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How far to the hospital? The effect of hospital closures on access to care

Thomas C. Buchmueller [a], Mireille Jacobson [b,*], Cheryl Wold [c]

[a] *University of California, Irvine and NBER, United States*
[b] *University of California, Irvine, United States*
[c] *Los Angeles County Department of Health Services, United States*

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Abstract

Do urban hospital closures affect health care access or health outcomes? We study closures in Los Angeles County between 1997 and 2003, through their effect on distance to the nearest hospital. We find that increased distance to the closest hospital increases deaths from heart attacks and unintentional injuries. This finding is robust to several sensitivity checks. We also find that, for residents with health insurance, increased distance shifts regular care towards doctor's offices. While most residents are otherwise unaffected, we find some evidence that seniors perceive more difficulty accessing care.

JEL classification: I11; I12; I18

Keywords: Hospital closure; Access to care

1. Introduction

Just prior to the November 2002 elections, Los Angeles County announced that without a US$ 350 million bailout it would be forced to close several area hospitals and clinics. High on the list of proposed closures were Harbor-UCLA and Olive View-UCLA Medical Centers, hospitals that serve a disproportionate share of the county's Medi-Cal and uninsured populations. Since Harbor-UCLA is a Trauma I center, its closure would mean the loss of significant trauma and emergency care services in the Los Angeles area. The passage of a ballot initiative (Measure B)

* Corresponding author. Tel.: +1 734 936 1321; fax: +1 734 936 9813.
E-mail address: mireille@uci.edu (M. Jacobson).

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Table 1
Hospital closures and openings in the Los Angeles region: 1998–2002

Year	Los Angeles County			Neighboring counties		
	Open start of year	Closed during year	Opened during year	Open start of year	Closed during year	Opened during year
1997	131	3	0	89	2	0
1998	128	6	1	87	2	0
1999	123	1	0	85	1	2
2000	122	0	0	86	2	2
2001	122	3	0	86	0	1
2002	119			87		

Source: OSHPD's Annual Utilization Report of Hospitals, 1997–2001 and 2002 Hospital Facility Listing. *Notes*: The neighboring counties are Orange, Ventura, Riverside and San Bernardino. General Acute Care (GAC) hospitals are all non-federal hospitals except psychiatric hospitals (acute or long term), chemical recovery hospitals and state correctional facilities. A GAC hospital is listed as having closed in 1998 if it appeared in the Utilization Report or Hospital Facility Listing for 1997 but not the 1998 or later years. Some hospitals that were incorrectly not listed in certain years were added back to the data; a detailed list of the reporting errors is available on request.

that increased tax funding for emergency rooms and trauma centers has reduced pressure on the county's health care system though, even with this additional funding, the system is still projected to face a deficit of between US$ 300 and 600 million over the next 3 years. Thus, the possibility of imminent hospital closures remains real.

The proposed closures are part of an ongoing trend in Southern California. Between 1997 and 2002, Los Angeles County lost roughly 10% of its initial 131 hospitals (see Table 1). Since 2002, nine more general acute care hospitals have closed in Los Angeles County. Although considerable media attention has focused on the potential deleterious effects of these closures on access to care and health outcomes, surprisingly little is known about the impact of urban hospital closures on patients.

The bulk of the literature on urban closures focuses on the supply side of the market: the determinants of closure and the operating efficiency of hospitals remaining in the market (see Lindrooth et al. (2003) for a good summary). This literature finds that nationally, closed hospitals tend to be small (fewer than 100 beds), financially distressed, for-profit facilities, operating with excess capacity. They also tend to offer fewer services, such as neonatal intensive care units, or specialized cardiac or emergency care services.

Scheffler et al. (2001) confirm that poor financial performance was a key predictor of hospital closures in California between 1995 and 2001. As shown in Table 2, the hospitals that closed in the Los Angeles Region between 1997 and 2002 were typical of closures on other dimensions as well. Most were small (the mean number of beds was 88) and all but two were for-profit facilities. Nonetheless, these hospitals did supply services that are critical for certain patients. For example, about two-thirds offered emergency medical or cardiac services, such as by-pass surgery or cardiac catheterization. The impact of closing this type of hospital on the health and health care needs of residents in surrounding areas is ultimately, however, an empirical question.

Research on the impact of closures on access to care and health more generally has focused largely on rural hospitals (Bindman et al., 1990; Mullner et al., 1989; Rosenbach and Dayhoff, 1995; Succi et al., 1997; US GAO, 1991). For obvious reasons, such studies have, at best, limited implications for considering the consequences of hospital closures in urban areas, such as Los Angeles County. A notable exception, Vigdor (1999), examines the effect of changes in the density

Table 2
Characteristics of closed hospitals affecting Los Angeles County residents

Facility name	Full year closed	Ownership type	GAC beds, 1997	Emergency services	Cardiac services
Newhall Community Hospital	1998	For-profit	N/A	N/A	N/A
Pioneer Hospital	1998	For-profit	99	Yes	Yes
Woodruff Community Hospital	1998	For-profit	66	Yes	Yes
Thompson Memorial Med Center	1999	For-profit	105	Yes	Yes
Kaiser Foundation—Norwalk	1999	Kaiser	96	No	No
Lakewood Regional Med Center[a]	1999	For-profit	69	No	No
North Hollywood Med Center	1999	For-profit	85	Yes	No
Rio Hondo Hospital[b]	1999	Non-profit	103	No	No
South Bay Medical Center	1999	For-profit	136	Yes	Yes
Washington Medical Center	2000	For-profit	81	Yes	Yes
West Valley Hospital	2002	Non-profit	139	Yes	Yes
Westside Hospital	2002	For-profit	57	Yes	No
Suncrest Hospital of Orange County[c]	1998	For-profit	74	No	No
Friendly Hills Regional Med Center[c]	1999	For-profit	113	Yes	No
Pacifica Hospital[c]	1999	For-profit	45	Yes	No

Source: OSHPD's Annual Utilization Report of Hospitals, 1997–2001 and 2002 Hospital Facility Listing.
[a] Clark Avenue Facility.
[b] Rio Hondo officially closed on 5/04/2001 but its license was suspended on 8/24/1998 and is thus coded as having effectively closed in 1999.
[c] Hospital is located in Orange County. Hospitals in counties bordering Los Angeles are included when they are the closest general acute care facility to some Los Angeles County residents.

of hospitals in Los Angeles County between 1984 and 1995 on rates of avoidable hospitalizations and deaths in the hospital from heart attacks and motor vehicle accidents. As pointed out by the author, however, by focusing solely on hospital discharges, Vigdor (1999) cannot assess the effect of closures on the health of people who never make it to the hospital in an emergency or on people who rely on hospital-based outpatient facilities.

In this paper, we address the gap in the literature by assessing the impact of hospital closures in the Los Angeles Region on perceived access to care, health care utilization and health outcomes. We consider closures through their effect on distance from a resident's home to the nearest hospital. Past work has shown that patients typically choose both providers and hospitals, particularly for acute conditions, based on proximity and reduced travel time (Cohen and Lee, 1985; Dranove et al., 1993; Hadley and Cunningham, 2004; Luft et al., 1990; McClellan et al., 1994; McGuirk and Porell, 1984). Thus, increased distance may translate to reduced access to care. While patients affected by a closure in urban areas often have other hospitals nearby,[1] the reduction in hospital supply may lead to increased crowding at and reduced access to the facilities remaining in the market. As a result, some may forgo or delay care when obtaining it becomes more difficult.

On the other hand, closures may have beneficial effects for nearby residents. Since closed hospitals are typically low-volume, poor-performers, health care outcomes might improve as residents are forced to choose among the remaining higher volume hospitals. Similarly, closures

[1] One recent study reports that in 90% of urban communities that experienced a closure between 1990 and 2000, emergency and inpatient care were still available within 10 miles of the closed facility (Department of Health and Human Services, Office of the Inspector General, 2003).

may shift some patients' usual source of care from a hospital to physician offices or community clinics, which are generally viewed as more appropriate sources of primary care.

To the extent that closures affect access and utilization, the effects are likely to vary with patient characteristics. We expect the effect of closures to be greatest on seniors, who travel shorter distances to the hospital (Vigdor, 1999) and low-income patients, who are both less likely to travel far and more likely to use the hospital as their "regular" source of care (Weissman and Epstein, 1994).[2] Indeed, in a study of hospital choice for maternal delivery in the San Francisco Bay Area, Phibbs et al. (1993) find that Medi-Cal women rely more heavily on public transportation than privately insured women and are therefore more sensitive to distance. Given the higher likelihood among Medi-Cal women of delivering at hospitals lacking specialized neonatal care and with worse perinatal outcomes, the authors interpret distance as a barrier to effective care for the poor. Similarly, in a study using national data, Currie and Reagan (2003) find that central-city black children living further from a hospital are less likely to have had a check-up, regardless of their insurance status. Both studies suggest that to the extent that closures force nearby residents to travel further for care, poor women and children may be particularly adversely affected.[3]

There may also be important differences with respect to health conditions. Even if the closure of weaker, poorer performing hospitals improves the average quality of hospitals, closures may have negative consequences for certain types of patients. In particular, outcomes for patients experiencing health events requiring fast attention, such as injuries sustained in an accident or a heart attack (AMI) may be affected by small changes in travel distance (Herlitz et al., 1993). In contrast, we would not expect urban hospital closures to affect mortality from conditions like chronic ischemic heart disease, where immediate emergency care is less relevant.

Our analysis is based on two distinct sources of health data: household surveys conducted by the Los Angeles County Department of Health Services (LACDHS) between 1997 and 2002, the period when most of the recent closures were occurring, and annual administrative zip code level mortality data from the California Department of Health Services. With the survey data, which provide information on residential location, we can assess the impact of changes in hospital proximity on perceived health care access and reported health care utilization. The administrative data give us an independent source of information on health outcomes that is not subject to self-reporting bias.

We find little effect of increased distance to the nearest hospital on outpatient utilization and the effects we do find are mixed. On a positive note, we find that increased distance is associated with an increase in the probability that respondents report a regular source of care as well as an increase in the likelihood that this care is sought at a doctor's office. Distance has little effect on perceived access to care in the population generally, though it is negatively related to perceived access for seniors, who may rely more on hospitals. Some models suggest that hospital closures may be associated with reductions in the probability that uninsured residents receive hospital-intensive diagnostic care, such as colon cancer screenings. Not surprisingly, we find no effect of

[2] Among children with a regular source of care in 1993, only 5% of the privately insured rely on a clinic or emergency room whereas 35% of publicly insured and 20% of uninsured do so (Bloom et al., 1997a). The breakdown by insurance status is similar for working-age adults (Bloom et al., 1997b).

[3] Patients whose choice of hospital is determined largely by proximity may be vulnerable in other, less easily measured ways. For example, several studies indicate that within the same medical center, patients who travel farther to receive elective care or even cancer treatment have better outcomes than similar patients with the same disease and receiving the same treatment, but who live nearby (Ballard et al., 1994; Goodman et al., 1997; Lamont et al., 2003).

increased distance on the receipt of other types of preventive care, such as HIV tests, pap smears, mammograms and flu shots that are commonly provided in non-hospital settings.

While the survey data point to some beneficial effects of hospital closures, the mortality data tell a different story. We find that increased distance to the nearest hospital is associated with an increase in deaths from acute myocardial infarction and unintentional injuries suffered at home, but not from other causes, such as cancer or chronic heart disease, for which timely care is less important. Thus, these results suggest that even the closure of small, private hospitals in large urban areas presents challenges to the provision of timely emergency care.

2. Data and methods

2.1. Data sources

Our area of study, Los Angeles County, has roughly 10 million residents spread over about 4000 square miles. The county is comprised of 88 cities, the largest of which, the city of Los Angeles, is home to roughly 40% of the county's population but covers only about 10% of its land. Another 10% of the population lives in unincorporated towns/areas.

We use several independent sources of data to study this area. The first is household level data from the Los Angeles County Health Surveys (LACHS), which were conducted by the LACDHS in 1997, 1999/2000 and 2002/2003. The LACHS, which surveys roughly 8000 adults, depending on the year, asks several questions on perceived access to care and self-reported utilization. Specifically, the survey asks whether the individual has a usual source of care (and where it is), how they perceive their access to care (very to somewhat difficult versus very to somewhat easy) and whether or not they have received several different types of preventive care (colon cancer screening, vaccines, HIV tests). In addition, it has detailed information about a respondent's health status, demographics, socio-economic status and medical insurance status. Importantly for this analysis, there is also information on the zip code of each respondent's residence, which allows us to link respondents to measures of distance to the nearest hospital.[4]

To examine the effect of distance to the nearest hospital on health outcomes, we use death reports from California's Department of Health Services. We use cause-specific mortality data from 1997 to 2001 to test for an effect of distance to the nearest hospital on mortality (by zip code of decedents' residence) from conditions for which access to timely emergency care is likely to be an important determinant of survival. Specifically, we examine the effect of distance on the number of deaths from heart attacks and unintentional injuries sustained at home.[5] We consider only injuries at home so as to avoid picking up accidents that occur far from a resident's closest hospital. As a specification check, we also consider the relationship between distance and both cancer and chronic ischemic heart disease deaths, outcomes that should be not be sensitive to how long it takes to get to the nearest hospital. A finding that distance is related to these outcomes would most likely be spurious, which would then cast doubt on our research design.

To calculate changes in travel distances from the center of each zip code in Los Angeles County to the address of the nearest hospital, we use data from the 1997 to 2001 Office of Statewide

[4] Zip codes are stripped from the publicly available LACHS data.

[5] Unintentional injuries are (1) transport accidents and their sequelae and (2) other external causes of accidental injury and their sequelae. These are covered by ICD-10 codes V01-X59 and Y85-Y86.

Health Planning's (OSHPD's) *Annual Utilization Report of Hospitals* 1997–2001, supplemented by OSHPD's 2002 *Hospital Facility Listing*. We consider hospitals in the entire Los Angeles Region, as the nearest hospital to county residents may lie in neighboring counties within the region. Since changes in proximity to the hospital for LA County residents came almost exclusively through closures, whereas residents from other parts of the region experience many changes due to openings as well as closures (see Table 1), we restrict our analysis to LA County residents.[6]

2.2. Econometric specification

We use a quasi-experimental design to examine how changes in driving distance from the population center of a zip code in Los Angeles County to the nearest hospital have affected perceived access, self-reported health care utilization and actual health outcomes among residents in that zip code.[7] Essentially, we compare changes in access or health among individuals in areas where hospitals closed to changes among otherwise similar individuals in areas where the availability of hospital services remained constant. One set of regressions uses the individual-level data from the LACHS, while another uses mortality data aggregated to the level of the zip code. For both types of data, the general form of the econometric specification is:

$$Y_{\mathrm{zt}} = \alpha\,\mathrm{distance}_{\mathrm{zt}} + X'\beta + \delta_{\mathrm{z}} + \gamma_{\mathrm{t}} + \varepsilon_{\mathrm{zt}} \tag{1}$$

where the dependent variable, *Y*, includes the measures of access, utilization and health outcomes just described. Control variables are represented by the vector *X*. The primary controls in the LACHS regressions are individual characteristics that are likely to affect medical care utilization and perceived access, such as income, health insurance coverage and health status. We also include some neighborhood characteristics, such as the number of community health clinics in a zip code and city-level unemployment rates.[8] Since clinics open and close frequently in order to service unmet health care needs, particularly those of vulnerable populations, clinic counts help capture community-wide changes in the supply of health services (US GAO, 1995; Royer, 2005). Similarly, city unemployment rates help control for any effect of local economic conditions on health.[9]

In our main specification, we include zip code fixed effects, δ_{z}, to account for time-invariant differences in demand that may exist across areas due to factors, such as the socioeconomic characteristics of the population. However, because hospital closures are quite rare, a possible disadvantage of this estimation strategy is that the model is identified by changes affecting a fairly small percentage of the population. Therefore, as an alternative specification, we estimate models

[6] LA County residents were affected by one opening, a Kaiser facility in Baldwin Park. Because it was located close to another neighborhood facility, Santa Rosa Hospital later called Legacy Hospital of San Gabriel Valley, distance from the two affected zip codes to the nearest hospital was essentially unchanged.

[7] The zip center coordinates from http://www.oseda.missouri.edu/uic/zip.resources.html are essentially a population-weighted average of the coordinates for the census blocks in a zip code area. They are virtually identical to the zip center coordinates given by both Yahoo!® Maps and MapQuest®.

[8] Annual unemployment rates are available through the California Economic Development Department's "Labor Force Data on Sub-County Areas in California." For cities missing unemployment rates, we use the county-year average. We also include an indicator for this substitution in the regressions. Clinics are listed in OSHPD's *Primary Care Clinic Listings*.

[9] Ruhm (2000, 2005) studies the relationship between health and state unemployment rates and finds reductions in mortality and improvements in health behaviors (e.g. physical inactivity and smoking) when the state economy weakens. Since these health improvements may occur partially through changes in leisure time, local unemployment rates may capture similar trends.

that replace the zip code dummies with city or "community" fixed effects, where the geographic unit is the city or town for areas outside of the city of Los Angeles and neighborhoods that are relatively homogeneous in terms of economic and demographic characteristics (e.g. Brentwood or Boyle Heights) are the unit within the city of Los Angeles. To the extent that these communities are relatively homogeneous with respect to demographics and other demand side variables, this specification exploits additional within-community differences in distance related to the location of all hospitals, not just those that closed or opened during the period of analysis. In all models, we also include year fixed effects, γ_t, to capture any county-wide trends in access and health.

Another possible limitation of (1) is that it assumes that the effect of distance is the same for all residents of an area, which clearly may not be the case. To the extent that uninsured patients are more likely to use emergency departments and hospital-based clinics as a source of primary care, we would expect them to be more strongly affected by the distance to the nearest hospital. Similarly, seniors and lower income people are likely to face higher transportation costs, which would translate to a larger effect of distance on access and utilization. In the models using the LACHS data, we test for these possible differential effects by estimating models in which the distance variable is interacted with separate indicators for Medi-Cal, Medicare and "private" insurance, where private insurance captures those with employer-sponsored, military or individually purchased health insurance policies. We also estimate models on the sub-sample of individuals reporting an annual household income of less than US$ 30,000, about 70% of median household in the county in 2000. To simplify the tables, we do not separately report results for the higher income group since they are typically not significantly different from the full sample results. In some cases, we also report results separately for all seniors as well as those reporting household income less than US$ 30,000. We do not include insurance interactions for this group since nearly all the seniors in our sample report Medicare coverage.

In the models estimated using the LACHS, the regressions are at the respondent level and are weighted by the inverse probability that the respondent was included due to the sampling design. The LACHS outcomes studied are all dichotomous: whether the usual source of care is an emergency room or hospital-based clinic, whether or not the respondent believes she has good access to care, and whether or not the person has received several types of preventive care or diagnostic tests. Because we are including zip code or community fixed effects, however, we use linear probability models to consistently estimate the effect of changes in distance on these outcomes.[10]

For our models of annual zip code deaths by cause, we use Poisson regression models to capture the non-negative count nature of the data. The Poisson model also allows us to include zip code fixed without introducing the incidental parameters problem common to other non-linear models (see Cameron and Trivedi, 1998, pp. 280–2). We include controls for total deaths, deaths by homicide (to proxy for the general risk of the neighborhood) and the age distribution of deaths (to proxy for the age structure of the neighborhood) as well as the number of health clinics in a zip code year. We also estimate specifications that include separate linear time trends for each zip code to account for demographic or economic shifts within a zip code that are not common across areas. We analyze the number of deaths rather than the death rate because we do not have

[10] We also estimated the LACHS regressions as probits; the results were very similar to the LPM results (see Buchmueller et al., 2004). We chose to report the LPM results because in cases where there the number of observations per zip code is small, the probit estimates may suffer from an "incidental parameters" problem and therefore be inconsistent. The main argument against the LPM specification is that the model's predictions can fall outside the [0, 1] interval. This is not a major issue for the outcomes we study because the sample means are not close to the boundary of this interval.

annual zip code level population data and any imputations based on changes in zip code level population from the 1990 and 2000 censuses will be captured in the linear, zip code specific time trends included in these models.[11]

To correct the serial correlation in the error terms, we estimate the standard errors in all LACHS models using a block bootstrap method (Efron and Tibshirani, 1994), which samples with replacement the full number of zip codes in (267) in our sample.[12] The standard errors are calculated as the standard deviation of the coefficient estimates from 200 bootstrap samples. Because the mortality models have few observations (5 years) within each block (335 zip codes) and too few observations per block increases the bias of the bootstrap method (Härdle et al., 2003), we correct these standard errors by allowing for an arbitrary correlation of the error terms at the zip code level (Bertrand et al., 2004).[13]

3. Results

3.1. Descriptive statistics: LACHS

Table 3 presents summary statistics for LACHS respondents overall, for those living in zip codes unaffected by closures, those living in affected zip codes before a change in distance and those living in affected zip codes after a change in distance. In addition to being directly relevant to our analysis that uses the LACHS, these figures also provide useful context for interpreting the zip code level mortality analysis.

For the full sample, the average driving distance to the nearest hospital is 2.65 miles. The figures in the second and third columns show that the average distance was initially similar for individuals living in zip codes that were affected by closures compared to individuals for whom the distance did not change. As shown in column 4, zip codes that experienced hospital closures during this period had an increase in driving distance to the nearest hospital of almost 2 miles, from an average driving distance of about 2.4–4.2 miles. Within this group, the change in distance associated with a closure ranged from roughly a tenth of a mile to about 5 miles.

Other initial differences between the two groups suggest the importance of controlling for individual characteristics and area fixed effects. The areas that lost hospitals are relatively affluent compared to the rest of the county. This is evident in the mean socioeconomic characteristics of respondents in zip codes that did and did not experience an increase in distance to the closest hospital. Those who faced a change were significantly more likely to be white (62% versus 39%), U.S. citizens (89% versus 78%), English-speaking (88% versus 76%) and have a college or post-graduate degree (40% versus 30%). Respondents in affected zip codes were also more likely to have private health insurance (58% versus 51%) and less likely to have Medi-Cal (2.5% versus 8.2%) and have slightly better self-reported health and access to care. These demographic and socioeconomic differences largely persist in the post-closure period (column 4).

[11] The correlation between zip code population from the 1990 and 2000 census is 0.97. As a sensitivity check, we performed this analysis (not shown here) on the set of zip codes with a 1990–2000 percentage population change between the 5th and 95th percentile. The results are virtually identical.

[12] We drop zip codes with six or fewer respondents across all survey years. The median and mean zip code remaining in the sample has about 100 respondents.

[13] Moreover, "clustering" performs well when the cross-sectional element of the panel, in this case the 335 zip codes, is large and the time element small (5 years); see Kezdi (2003).

Table 3
Los Angeles County Health Survey summary statistics

	Overall	By change in distance to closest hospital		
		No change	Pre-change	Post-change
Hospital distance variable				
Miles to closest hospital (driving)	2.65 (0.018)	2.54 (0.019)	2.35 (0.055)	4.15 (0.068)
Outcome variables				
Has regular source of care	0.781	0.782	0.753	0.817
Go to MD's office for care	0.621	0.616	0.621	0.703
Go to ER or outpatient clinic for care	0.133	0.138	0.102	0.085
Ease of access to health care	0.714	0.708	0.708	0.776
Colon cancer screen (age >50)	0.438	0.436	0.449	0.464
Received HIV test (age <65)	0.358	0.365	0.350	0.291
Health insurance status				
Insured—private, empl, military	0.521	0.512	0.578	0.610
Medi-Cal, non-Medicare	0.077	0.081	0.025	0.050
Medicare	0.122	0.121	0.119	0.122
Individual characteristics				
Gender (male)	0.407	0.406	0.444	0.436
Age	43 (0.11)	43 (0.12)	43 (0.51)	44 (0.43)
Race				
Hispanic	0.376	0.390	0.222	0.0287
White	0.411	0.391	0.621	0.556
Black	0.100	0.109	0.041	0.032
Asian	0.094	0.091	0.093	0.100
Pacific Islander	0.008	0.008	0.014	0.008
American Indian	0.005	0.004	0.003	0.005
Other	0.003	0.003	0.005	0.010
Citizen	0.784	0.777	0.885	0.847
Survey taken in				
English	0.770	0.763	0.877	0.838
Spanish	0.200	0.209	0.096	0.130
Mandarin	0.010	0.009	0.012	0.011
Cantonese	0.006	0.006	0.001	0.004
Korean	0.008	0.007	0.012	0.010
Vietnamese	0.005	0.004	0.001	0.005
Household income				
US$ <10,000	0.115	0.121	0.066	0.064
US$ 10,000–20,000	0.179	0.185	0.148	0.132
US$ 20,000–30,000	0.119	0.122	0.120	0.103
US$ 30,000–40,000	0.099	0.100	0.131	0.093
US$ 40,000–50,000	0.080	0.081	0.091	0.079
US$ 50,000–75,000	0.119	0.116	0.168	0.146
US$ >75,000	0.154	0.149	0.173	0.239
Missing	0.136	0.126	0.103	0.144
Education level				
8th grade or less	0.094	0.096	0.047	0.053
9–12th grade	0.102	0.107	0.049	0.075
HS graduate	0.213	0.215	0.206	0.204
Some college	0.278	0.279	0.295	0.274
College grad	0.203	0.196	0.270	0.257
Post-grad degree	0.110	0.107	0.133	0.137

Table 3 (*Continued*)

	Overall	By change in distance to closest hospital		
		No change	Pre-change	Post-change
Working status				
Full-time	0.463	0.463	0.531	0.470
Part-time	0.109	0.109	0.121	0.115
Hours unknown	0.005	0.005	0.001	0.006
Not working	0.161	0.163	0.151	0.140
Retired	0.127	0.126	0.119	0.139
Homemaker	0.095	0.095	0.014	0.123
Unknown	0.038	0.039	0.060	0.018
Marital status				
Married	0.479	0.475	0.449	0.533
Co-habitating	0.072	0.075	0.046	0.051
Widowed	0.064	0.064	0.052	0.066
Divorced	0.100	0.100	0.125	0.093
Separated	0.035	0.036	0.033	0.026
Never married	0.250	0.251	0.295	0.229
Household size	3.09 (0.011)	3.12 (0.012)	2.67 (0.051)	3.04 (0.044)
Health status and behaviors				
BMI	24.0 (0.054)	24.1 (0.058)	23.6 (0.228)	24.1 (0.204)
Self-assessed health: 1 = excellent, 5 = poor	2.50 (0.007)	2.51 (0.008)	2.35 (0.034)	2.34 (0.028)
Diabetes	0.063	0.064	0.043	0.059
Arthritis	0.173	0.174	0.168	0.168
Heart disease	0.060	0.060	0.046	0.064
Smoke cigarettes	0.160	0.162	0.209	0.144
Observations	23503	21012	925	1566

Notes: Standard errors for continuous variables are given in parenthesis. With the exception of the hospital data which are from OSHPD, data are from the (adult) Los Angeles County Health Survey (LACHS) 1997, 1999/2000 and 2002/2003. Miles to closest hospital is defined as the MapQuest® driving distance from the population centroid or in some cases the physical center of a zip code to the closest hospital. Insurance and health status questions refer to time of survey. BMI is defined as weight in kilograms divided by the square of height in meters. Self-assessed health status ranges from excellent (1) to poor (5). Colon cancer screens include colonoscopies and sigmoidoscopies among respondents 50 and over in their lifetime. All other questions about diagnostic exams refer to the past 2 years. The flu shot refers to this year.

Tables 3 also presents the outcomes we examine.[14] The figures show that nearly over three-quarters of respondents report having a usual source of care and that for the vast majority that source was a physician's office (62% of all respondents or 80% of those with a usual source of care). The fact that only 13% of the sample report that an ER or hospital clinic is their usual source of care suggests that the effect of closures on access to primary care may be limited. Comparing columns 3 and 4, it appears that hospital closures were associated with a shift in patients' usual source of care, to physician offices away from emergency rooms or hospital-based outpatient clinics, though these changes are not statistically significant. Simple mean comparisons also suggest that, with the exception of HIV screening, other dimensions of care and access seem to have improved after a hospital closure.

[14] The measures of usual source of care and perceived access are defined for the full sample. In contrast, some of the questions concerning the receipt of diagnostic care were targeted to specific relevant populations—e.g. individuals over age 50 for colon cancer screening.

Table 4
Marginal effect of distance to the closest hospital on source of care

Sample	Full sample		HH income US$ <30,000	
Panel A: have a place where regular care is sought				
Driving distance to hospital (miles)	0.017 (0.010)	0.017 (0.010)	0.027 (0.015)	0.028 (0.016)
Miles × private insurance	–	0.0002 (0.004)	–	0.001 (0.006)
Miles × Medi-Cal	–	−0.005 (0.005)	–	−0.003 (0.005)
Miles × Medicare	–	−0.001 (0.004)		−0.004 (0.005)
Private insurance	0.259 (0.011)	0.259 (0.015)	0.260 (0.014)	0.258 (0.020)
Medi-Cal	0.254 (0.012)	0.266 (0.018)	0.264 (0.014)	0.271 (0.019)
Medicare	0.237 (0.015)	0.240 (0.018)	0.248 (0.017)	0.256 (0.021)
Observed probability	0.781	0.781	0.714	0.714
Observations	22338	22338	11916	11916
Panel B: respondent goes to ED or outpatient clinic if care is needed				
Driving distance to hospital (miles)	−0.001 (0.006)	0.002 (0.006)	0.0008 (0.010)	0.001 (0.010)
Miles × private insurance	–	−0.004 (0.002)	–	−0.007 (0.003)
Miles × Medi-Cal	–	−0.004 (0.005)	–	−0.003 (0.006)
Miles × Medicare	–	−0.003 (0.003)	–	−0.004 (0.005)
Private insurance	−0.077 (0.006)	−0.067 (0.009)	−0.108 (0.010)	−0.091 (0.012)
Medi-Cal	−0.067 (0.015)	0.077 (0.022)	0.043 (0.017)	0.049 (0.024)
Medicare	−0.068 (0.013)	−0.060 (0.016)	−0.088 (0.018)	−0.080 (0.022)
Observed probability	0.133	0.133	0.197	0.197
Observations	22020	22020	11715	11715
Panel C: respondent goes to a doctors office if care is needed				
Driving distance to hospital (miles)	0.017 (0.010)	0.013 (0.010)	0.017 (0.012)	0.013 (0.013)
Miles × private insurance	–	0.008 (0.003)	–	0.009 (0.005)
Miles × Medi-Cal	–	0.0002 (0.006)	–	0.0002 (0.007)
Miles × Medicare	–	0.003 (0.004)	–	0.003 (0.004)
Private insurance	0.343 (0.013)	0.322 (0.014)	0.343 (0.013)	0.322 (0.018)
Medi-Cal	0.213 (0.017)	0.213 (0.022)	0.213 (0.017)	0.213 (0.025)
Medicare	0.326 (0.020)	0.319 (0.020)	0.326 (0.020)	0.319 (0.022)
Observed probability	0.619	0.619	0.486	0.486
Observations	22276	22276	11836	11836

Notes: Standard errors are computed using a block-bootstrap with 200 bootstrap samples and are shown in parenthesis. Regressions include survey year and zip code fixed effects and are estimated using survey weights. They also control for age, age-squared, gender, household size and its square, race (7 categories), citizenship, language the survey was taken in (6), household income (6), education (6), current employment status (6) and marital status (6).

3.2. Linear probability regression results: access to care and preventive screening

The linear probability regression results for these outcomes are reported in Table 4 (usual source of care and place of care), Table 5 (perceived access) and Table 6 (diagnostic care). All “source of care” and access questions are point in time, without reference to a time period. For sake of brevity, we do not report the estimated effects of health-related controls but these are interesting in their own right and are available from the authors upon request.[15]

[15] For example, these results confirm that more vulnerable patients (e.g. those with poor self-reported health status and diabetics) are more likely to use an ED or hospital based clinic as their regular source of care. Similarly, those with poor self-reported health status and arthritics report more difficulty accessing care.

Table 5
Marginal effect of distance to the closest hospital on reported ease of access to health care services

Sample	Full		HH income US$ <30,000		Age ≥65	
					All	Inc US$ <30,000
Distance to hospital (miles)	0.001 (0.010)	0.002 (0.010)	−0.012 (0.018)	−0.015 (0.018)	−0.040 (0.022)	−0.052 (0.036)
Miles × private insurance	–	−0.001 (0.003)	–	0.005 (0.005)	–	–
Miles × Medi-Cal	–	0.008 (0.005)	–	0.011 (0.006)	–	–
Miles × Medicare	–	−0.001 (0.004)	–	0.004 (0.005)	–	–
Private insurance	0.290 (0.009)	0.291 (0.012)	0.316 (0.012)	0.307 (0.017)	0.107 (0.043)	0.106 (0.053)
Medi-Cal	0.264 (0.013)	0.243 (0.020)	0.288 (0.016)	0.262 (0.022)	0.013 (0.084)	0.073 (0.098)
Medicare	0.289 (0.017)	0.290 (0.029)	0.299 (0.020)	0.290 (0.024)	0.100 (0.043)	0.080 (0.042)
Probability	0.716	0.716	0.605	0.605	0.887	0.870
Observations	21848	21848	11568	11568	2807	1858

Notes: Standard errors are computed using a block-bootstrap with 200 bootstrap samples and are shown in parenthesis. Regressions include survey year and zip code fixed effects and are estimated using survey weights. They also control for age, age-squared, gender, household size and its square, race (7 categories), citizenship, language the survey was taken in (6), household income (6), education (6), current employment status (6) and marital status (6).

Table 6
Marginal effect of distance to the closest hospital on colon cancer screening

Sample	Full sample		HH income US$ <30,000	
Panel A: models using zip code fixed effects				
Distance to hospital (miles)	0.008 (0.020)	−0.009 (0.021)	0.013 (0.032)	−0.001 (0.026)
Miles × private insurance	–	0.018 (0.006)	–	0.022 (0.009)
Miles × Medi-Cal		0.017 (0.015)		0.022 (0.017)
Miles × Medicare		0.018 (0.007)		0.018 (0.010)
Private insurance	0.099 (0.021)	0.057 (0.025)	0.104 (0.027)	0.052 (0.036)
Medi-Cal	0.077 (0.035)	0.037 (0.052)	0.077 (0.037)	0.028 (0.050)
Medicare	0.084 (0.020)	0.041 (0.027)	0.089 (0.027)	0.047 (0.036)
Observed probability	0.441	0.441	0.421	0.421
No. of observations	6971	6971	3754	3754
Panel B: models using community fixed effects				
Distance to hospital (miles)	0.002 (0.004)	−0.012 (0.006)	0.002 (0.006)	−0.013 (0.008)
Miles × private insurance	–	0.016 (0.003)	–	0.019 (0.010)
Miles × Medi-Cal		0.017 (0.016)		0.022 (0.016)
Miles × Medicare		0.016 (0.008)		0.018 (0.010)
Observed probability	0.441	0.441	0.421	0.421
No. of observations	6971	6971	3754	3754

See notes to Table 4.

Panel A of Table 4 looks at whether the respondent has a "particular regular source of care where he/she goes most often." Columns 1 and 3 consider the main distance effect alone for the full and low-income sub-samples; columns 2 and 4 include the interactions between health insurance ("private", Medi-Cal or Medicare) and distance. All results are for the model with zip code fixed effects. The models with community fixed effects (available upon request) yield similar results.

In both the full and low-income samples, hospital closures appear to increase the probability of reporting a usual source of care. The effect is largest for the low-income sample, where a 1 mile increase in distance to the nearest hospital is associated with an almost 4% (or 2.7 percentage points off a base of 71.4%) increase in the likelihood of reporting a particular place where care is sought. One possible explanation for this result is that around the time of a closure, county or city authorities may have increased outreach efforts to encourage residents who had relied on the hospital emergency room or its outpatient clinic (but perhaps did not view these as a "usual" source of care) to find an alternative. Similarly, residents may have responded to the considerable media attention given to hospital closures by identifying an alternative source of care. Physicians or clinics that serve low-income populations may have also seen closures as a business opportunity and either moved into the area or marketed their services more aggressively. Finally, given that we only have 3 years of data, we cannot rule out that these results simply reflect differential improvements in access to care across the closure and non-closure areas that might have occurred even in the absence of hospital closures.

The results in Panels B and C, however, suggest a mechanism by which any increases in reporting a regular source of care might have occurred. Although quite imprecisely estimated, Panel B suggests that for insured patients, increased distance to the hospital may be associated with a decrease in reliance on an ED or clinic when sick. Panel C suggests that closures coincide with an increased reliance on a physician's office, particularly for insured residents.

In both the full and low-income samples, the results suggest a roughly 1–2% increase in reporting that a doctor's office is the usual place of care. Both the magnitude and precision of the interactions, suggest that these effects are concentrated among those with private health insurance.

Table 5 takes the analysis a step further by asking how closures and the subsequent shifting of sources of care affect perceived access. Although this variable is subjective and may not be well-defined across respondents, we find it interesting nonetheless to examine how it has changed with increased distance to the hospital. In addition to considering the full and low-income samples, we also study all respondents aged 65 and over (column 5) as well as those seniors reporting household income under US$ 30,000 (column 6).

Across all residents, increased distance appears to have little effect on perceived access to care. This is not surprising, given that such a small fraction of the overall population rely on hospitals as their usual source of care. However, the results for the "vulnerable" subpopulations offer some support for the hypothesis that the impact of closures should be felt most acutely by populations that have difficulty traveling farther for care. For adults over age 65, we find that a 1 mile increase in distance to the hospital is associated with a roughly 4 percentage point decline in ease of access to care, statistically distinguishable from 0 below the 10% level. Similarly, the point estimates for the low-income respondent suggest a 1-mile increase in the distance to the nearest hospital results in a roughly 2% decrease in ease of obtaining health care for those without health insurance, though this effect is imprecisely estimated. As with the source of care regressions, the results for models using community fixed effects yield qualitatively similar results, although they are even less precisely estimated.

While reported source of care and perceived access are clearly important, we care ultimately about the effect of hospital closures on health services utilization and health outcomes. Therefore, we examine the effect of changes in the distance to the nearest hospital on use of health care services. Table 6 considers colon cancer screenings (colonoscopy or sigmoidoscopy) in individuals over 50.[16] We do not find a statistically significant effect of distance when we control for zip code fixed effects (Panel A).

However, the results from less restrictive specifications that controls for community fixed effects suggest a statistically significant negative effect of distance on screening for the uninsured (Panel B, columns 2 and 4). Estimates from the full sample indicate that a 1 mile increase in distance is associated with a decline of 1.2 percentage points in the probability that an uninsured respondent reports having been screened. This effect is fully offset by health insurance.

Finally, in models not reported, we examined the effect of distance on HIV tests for adults under age 65, PAP smear tests for women 18 and over, mammograms for women over 40, and flu shots for seniors, all within the last 2 years. Compared to the other types of screening, there is less reason to expect an effect of distance on these outcomes. PAP smears and HIV tests can be administered anywhere and are commonly provided in physicians' offices. Similarly, mammograms are often given in dedicated, non-hospital based facilities and flu shots are provided at an even broader range of places. It is not surprising, then, that for these outcomes we find no discernable effect of distance to the nearest hospital.

[16] The question was asked of those 40 and older in 1997 but only those 50 and older in subsequent surveys. The reference period for this question changes after the 1997 survey, from asking about tests in the last 2 years to tests at any point in time. This change biases us against finding a deleterious effect as the 1997 baseline (pre-closure) rate of screening in a zip code is by definition less than (or equal to) the lifetime screening rate.

Table 7
Summary statistics for general mortality data, 1997–2001

	Overall mean	Distance to closest hospital		
		No change	Pre-change	Post-change
Miles to closest hospital (driving)	3.01 (0.099)	2.93 (0.099)	2.12 (0.163)	4.52 (0.618)
# Community health clinics	0.709 (0.028)	0.739 (0.031)	0.678 (0.110)	.355 (0.056)
Total deaths	173 (2.97)	175 (3.26)	195 (9.44)	135 (8.01)
Unintentional injury deaths at home	1.33 (0.036)	1.36 (0.039)	1.29 (0.164)	1.07 (0.111)
AMI deaths	13.9 (0.272)	14.1 (0.295)	15.9 (1.09)	10.4 (0.748)
Chronic ischemic heart disease deaths	23.7 (0.433)	23.7 (0.466)	31.1 (1.90)	18.9 (1.26)
Lung cancer deaths	9.44 (0.182)	9.41 (0.196)	11.5 (0.734)	8.76 (0.608)
Colon cancer deaths	3.31 (0.071)	3.31 (0.076)	4.25 (0.299)	2.87 (0.225)
Homicides	2.96 (0.116)	3.17 (0.130)	1.36 (0.171)	1.09 (0.131)
Zip-year observations	1675	1495	59	121

Source: California Department of Health Services, Death Statistical Master Files.

3.3. Sensitivity tests

One potential problem with our main analyzes is that, as demonstrated by the descriptive statistics in Table 3, people in zip codes not affected by hospital closures are different from those in affected zip codes and thus do not necessarily make a good control group. To the extent that these differences are not constant, our area-level fixed effects will not fully control for them. One way to more fully control for this heterogeneity is to restrict the analysis to respondents living in zip codes where there was a change in distance to the nearest hospital at some point during the sample period. Restricting the sample in such a manner cuts the number of observations down by about 85%, from about 22,000 to almost 3000 respondents, and in some cases reduces the precision of the results. In general, however, the results are qualitatively similar, suggesting that increased distance to the nearest hospital increases the likelihood of reporting a regular source of care. As in the main results, we find a decline in perceived access to care for seniors of about 3–4 percentage points for each additional mile to the hospital, although with only 300 observations for this group we cannot reject zero effect. Consistent with although larger in magnitude than the neighborhood fixed effect models, these results also indicate a decrease in colon cancer screening for the uninsured of 6 percentage points (p-value <0.078) for each additional mile to the nearest hospital.

3.4. Zip code level analysis of mortality

We now turn to our analysis of mortality by cause, using zip code level administrative data. Increased distance to the nearest hospital may affect survival probabilities of area residents experiencing acute conditions for which prompt medical attention is crucial. To test for such effects, we consider the effect of distance on mortality from acute myocardial infarction and unintentional injuries. As a check on these results, we estimate similar models on outcomes where emergency care is much less important: chronic heart disease and cancer.

The summary statistics zip code level death counts by cause are reported in Table 7. As with the LACHS, we report these figures for the overall sample, those living in zip codes unaffected by hospital closures, those living in affected zip codes before a closure and those living in affected zip codes after a closure. Consistent with the differences in SES found in the other data set, there were fewer homicide deaths in zip codes experiencing a change in distance. In contrast, over the whole period there was no significant difference in total deaths from heart attacks or unintentional injuries. However, the number of deaths overall and by all reported causes declined in zip codes experiencing an increase in distance to the nearest hospital (columns 3 and 4). In contrast, deaths from all reported causes in zip codes unaffected by closures remained remarkably constant over this period (not shown here). Thus, to the extent that our models do not fully capture these differential trends, we risk understating any negative effects of delays in the receipt of timely emergency care.

The mortality regression results are reported in Table 8. Panel A considers the simple effect of changes in distance to the closest hospital on deaths by type. Panel B adds some flexibility to the model by allowing for a separate post-closure intercept (or a level effect) for the impacted zip codes.

As shown in Panel A, for AMI deaths, the basic model indicates that a 1 mile increase in distance leads to a nearly a 6.5% increase in the number of deaths or just under one additional death from a heart attack per zip code year (column 1). The magnitude of this effect is almost identical when we include zip code specific time trends (column 2). This result is consistent with the American Heart Association (2003) claim that the survival probability after cardiac arrest decreases by 7–10% for every minute without treatment.

We also find increases in deaths from unintentional injuries sustained at home. A 1 mile increase in distance to the nearest hospital is associated with an 11–20% increase in the number of deaths from unintentional injuries, with the larger effect coming from the model with the zip code specific time trends. Although these magnitudes seem large, deaths from injuries sustained at home are quite rare. Thus, these magnitudes imply that the typical hospital closure is associated with fewer than 0.5 additional deaths per zip code year.

In contrast, the estimated relationship between changes in distance to the nearest hospital and deaths from chronic heart disease or cancer[17] are rather imprecisely estimated, and in the case of chronic heart disease is of opposite sign. Though not presented here for sake of brevity, this invariance to distance is also found for deaths from chronic pulmonary obstructive disorder (COPD), Alzheimer's disease and diabetes. We take these null results as some confirmation that the heart attack and unintentional injury findings are picking up real effects of changes in distance to the nearest hospital rather than some unobserved factors affecting deaths more generally in these zip codes.

Panel B largely confirms the findings from our basic model, that the increased distance to the closest hospital induced by closures is associated with increases in deaths from heart attacks and unintentional injuries but has no clear impact on other causes of death. Interestingly, however, these increases appear to be partially offset by reductions caused by closing these poor performing hospitals. In other words, closures may induce some survival benefit by forcing people to be transported to higher volume hospitals, with more sophisticated equipment and more experienced staff. This model should be taken only as suggestive, as we likely do not have enough variation to estimate both the effect of closures and a distinct effect of distance. In other words, given how few hospitals closed, it is not clear that we can distinguish a "pure closure" effect,

[17] We also estimated separate models for lung and colon cancer. In the colon cancer models, the coefficient on distance is negative, though not statistically significant. The results for lung cancer are small (1–2%) but borderline significant, suggesting that these deaths may increase with distance to the hospital. Unlike the results for AMI or unintentional injuries, however, these results decrease in both magnitude and precision when we limit the sample to zip codes that had at least 10 deaths of any cause in a given year. This suggests that the lung cancer results may be driven by outliers.

Table 8
Poisson models of death counts: percentage change in deaths due to a mile increase in distance to the hospital in Los Angeles County

	AMI		Unintentional injuries, home		Chronic heart disease		All cancer	
Panel A: changes in distance								
Miles	6.45 (1.89)	7.17 (4.20)	11.7 (6.45)	20.4 (12.8)	−1.34 (1.33)	−1.82 (3.35)	0.85 (0.61)	2.14 (1.67)
Zip trends	No	Yes	No	Yes	No	Yes	No	Yes
Mean deaths	14	14	1.3	1.3	24	24	39	39
Observations	1675	1675	1675	1675	1675	1675	1675	1675
Panel B: separate effect of distance and closure								
Miles	11.4 (4.90)	17.9 (6.46)	55.1 (20.8)	80.6 (39.2)	−0.30 (0.65)	0.37 (1.68)	−0.48 (0.84)	0.02 (1.45)
Closure	−11.0 (10.1)	−22.7 (12.8)	−52.7 (13.6)	−60.8 (18.2)	−2.37 (3.77)	−8.13 (5.73)	6.28 (3.10)	9.09 (6.50)
Zip trends	No	Yes	No	Yes	No	Yes	No	Yes
Mean deaths	14	14	1.3	1.3	24	24	39	39
Observations	1675	1675	1675	1675	1675	1675	1675	1675

Notes: Standard errors are cluster-adjusted by zip code and shown in parenthesis. The key independent variable is the driving distance from each zip code population center to the closest hospital in a given year. All models also control for total deaths, deaths by homicide, the age distribution of deaths and the number of community health clinics, all at the zip code year level. They also include zip code and year fixed effects. Where indicated, zip code specific time trends are also included. Zip codes with fewer than five deaths in any given year are excluded as are zip codes that do not have any deaths in all years. Since the mean of the dependent variable in a Poisson regression model is parameterized as $\mu_i = \exp(X_i'\beta)$, the percentage change in expected deaths from a unit change in distance is given by $100 \times [\exp(\beta_k) - 1]$.

Table 9
Specification checks of Poisson models of death counts

	AMI		Unintentional injuries, home		Chronic heart disease		All cancers	
Panel A: all deaths in LA County zip codes, controlling only for total deaths								
Miles	6.01 (1.88)	6.56 (4.12)	14.1 (6.26)	13.03 (2.43)	−1.55 (1.25)	−2.02 (3.37)	0.56 (0.64)	1.77 (1.90)
Zip trends	No	Yes	No	Yes	No	Yes	No	Yes
Panel B: deaths in LA County zip codes where closest hospital is not a Kaiser								
Miles	6.87 (1.96)	9.63 (3.42)	12.2 (6.71)	23.7 (13.4)	−1.43 (1.35)	−2.05 (3.30)	0.86 (0.62)	2.41 (1.71)
Mean deaths	14	14	1.3	1.3	24	24	39	39
Observations	1615	1615	1615	1615	1615	1615	1615	1615
Panel C: deaths in LA zip codes where closest hospital had an ED								
Miles	8.21 (1.98)	8.45 (5.36)	7.99 (7.28)	19.2 (21.1)	−1.19 (1.36)	−1.35 (4.041	1.25 (0.76)	1.03 (1.83)
Mean deaths	9.5	9.5	3.6	3.6	16	16	39	39
Observations	1260	1260	1260	1260	1260	1260	1260	1260
Panel D: all deaths as a function of distance to the closest ED								
Miles	0.32 (2.06)	3.93 (2.54)	3.28 (6.88)	−0.64 (11.4)	−0.76 (1.17)	−2.29 (1.73)	0.47 (0.70)	−0.22 (1.08)
Mean deaths	9.5	9.5	3.6	3.6	16	16	39	39
Observations	1675	1675	1675	1675	1675	1675	1675	1675
Panel E: deaths in zip codes affected by closures								
Miles	8.23 (2.21)	9.36 (3.72)	39.0 (11.5)	31.3 (19.9)	−0.91 (1.60)	−1.83 (3.99)	0.92 (0.84)	0.54 (1.34)
Mean deaths	12	12	1.3	1.3	23	23	39	39
Observations	180	180	180	180	180	180	180	180

Notes: Standard errors are cluster-adjusted by zip code and shown in parenthesis. The key independent variable is the driving distance from each zip code population center to the closest hospital in a given year. All models also control for total deaths, deaths by homicide, the age distribution of deaths and the number of community health clinics, all at the zip code year level. They also include zip code and year fixed effects. Within each set of cause of death results, the second column also includes zip code specific time trends. Zip codes with fewer than five deaths in any given year are excluded, as are zip codes that do not have any deaths in all years. Since the mean of the dependent variable in a Poisson regression model is parameterized as $\mu_i = \exp(X_i'\beta)$, the percentage change in expected deaths from a unit change in distance is given by $100 \times [\exp(\beta_k) - 1]$.

as captured by the closure dummy, from a non-linear effect of distance or from an effect of outliers.

3.5. Sensitivity tests

Table 9 shows results from several sensitivity tests that broadly confirm the basic mortality findings. First, to test the sensitivity of our results to the choice of controls, we re-estimated the mortality models but only included total annual deaths in a zip code, zip code and year fixed effects, and in some specifications, zip code-specific time trends. The results from these shorter regressions (Panel A) are almost indistinguishable from those in the fully specified models.

We next excluded from our sample the 12 zip codes where Kaiser was the closest hospital at some point during the sample period since Kaiser facilities are typically not available to the broad public. Not surprisingly, given how few zip codes are dropped, the results (Panel B) are again almost identical to those in Table 8, although the AMI results with zip code specific time trends suggests a slightly larger (9.6%, p-value <0.005) increase in AMI deaths.

We took two approaches to testing whether our results were capturing the effects of changes in timely access to urgent or emergency care services. We first eliminated from the sample all zip codes where the closest hospital did not have an emergency room (Panel C). Doing so reduces the sample size by 25%, but does not materially affect the results. Here again, the estimates are quite similar to and not statistically significantly different from the main results in Table 8.

We next used the full sample and, rather than eliminating zip codes, changed our definition of closures to be limited to the closure of EDs. These results (Panel D) are quite imprecisely estimated. Based on the 95% confidence intervals of the estimated effects, we cannot reject the results from our models in Table 8 but neither can we reject zero. One reason for this imprecision may be that since we cannot identify based on our current data where patients of different types are taken and treated nor how hospitals change their services on the intensive margin, e.g. by scaling up or scaling down their ED's, this new coding of closures may be somewhat arbitrary. In contrast, when we consider hospital closures, we are clearly capturing the loss of an entire general service medical facility.

Lastly (in Panel E), we restricted the sample to zip codes where there was a change in distance to the nearest hospital at some point during the sample period. As in the LACHS models, we did this because the control group differs in many important ways (for example, insurance status, income and so on) from the group affected by closures. Despite the considerable reduction in sample size caused by this restriction, the magnitudes of the estimated impacts of a 1 mile increase in distance to the hospital on deaths from AMI and unintentional injuries are virtually the same as in our full model and in the main specification (without zip code specific time trends) are statistically significant below the 1% level.

4. Conclusions

While urban communities across the country have experienced a string of small hospital closures over the past decade, Los Angeles County is unique in just how many closures have occurred. Should excess hospital capacity continue to grow in other urban areas, however, the Los Angeles experience may become more common. The present study will provide useful lessons for these communities.

Like past work showing that urban hospital closures improve the efficiency of the health care system by shifting care to lower cost facilities (Lindrooth et al., 2003), we find that hospital closures may shift care to doctor's offices, generally considered an appropriate and cost-effective source of regular care (Baker and Baker, 1994). Although these efficiency savings from hospital closures are extremely important, they tell only part of the story.

We find some evidence that proximity to a hospital influences perceived access to care for the more vulnerable residents in Los Angeles County. Specifically, seniors, who tend to rely more on hospitals, report more difficulty accessing care as a result of closures. Although imprecisely estimated, this result is found across samples and specifications. The subjective nature of this outcome makes it somewhat difficult to interpret. A widely publicized hospital closure may give nearby residents the impression that their access to care has deteriorated, even if there is little change in their actual use of care. However, the fact that the same group reports a decline in colon cancer screening suggests that there may be something real behind the change in perceived access. Nonetheless, these results should be taken as suggestive. A small sample and changes in the question across surveys, in the case of colon cancer screening, prevent us from obtaining good estimates of these effects.

Using separate administrative data, we also find evidence that increased distance to the nearest hospital is associated with higher mortality counts from emergent conditions, such as heart attacks and possibly from unintentional injuries. These results are quite robust across sensitivity checks, although the weakness of the results using changes in distance to the nearest emergency department suggests that they should be interpreted with some caution. That we consistently find no impact of closures on causes of mortality that should be unaffected by timely access to care, however, provides additional support for the conclusion that the results for heart attacks and injuries reflect a real effect of hospital closures and not spurious correlation. Should they hold up to further investigation, these results suggest that social welfare may be increased by promoting low-cost, non-hospital based ways of treating emergent conditions after a local hospital closure.

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