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HOW FAR TO THE HOSPITAL?
THE EFFECT OF HOSPITAL CLOSURES ON ACCESS TO CARE

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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 nearest hospital shifts regular care away from emergency rooms and outpatient clinics to doctor's offices. While most residents are otherwise unaffected by closures, lower-income residents report more difficulty accessing care, working age residents are less likely to receive HIV tests, and seniors less likely to receive flu shots. We also find some evidence that increased distance raises infant mortality rates and stronger evidence that it increases deaths from unintentional injuries and heart attacks.

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Introduction

Just prior to the November 2002 elections, Los Angeles County announced that without a $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) 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 $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 percent of its initial 133 hospitals (see Table 1). Since 2002, Tenet Healthcare Corporation, an owner of several of these hospitals, has announced additional closures in the area (Hymon 2004, Vrana 2003). Although considerable media attention has focused on the potential deleterious effects of hospital closures on access to care and health outcomes in Los Angeles County, 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 (see Lindrooth et al. 2003 for a good summary) and the operating efficiency of hospitals remaining in the market (Lindrooth et al. 2003).[1]

[1] Scheffler et al. (2001) specifically studies the causes of hospital closures in California between 1995 and 2000. Not surprisingly, poor financial performance is a key predictor of closure.

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 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, actual 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 shows that patients typically choose both providers and hospitals, particularly for acute conditions, based on proximity and reduced travel time (McGuirk and Porell 1984, Cohen and Lee 1985, Dranove et al. 1993, McClellan et al. 1994). Thus, increased distance may translate to reduced access to care. While patients affected by a closure in urban areas often have other hospitals nearby, the reduction in hospital supply may lead to increased crowding at and reduced access to the facilities remaining in the market.[2] As a result, some may forgo or delay care when obtaining it becomes more of a hassle.

[2] One recent study reports that in 90 percent 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).

On the other hand, it is possible that closures may have beneficial effects on patients who are directly affected. 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 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).[3] 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.[4]

[3] Among children with a regular source of care in 1993, only 5 percent of the privately insured rely on a clinic or emergency room whereas 35 percent of publicly insured and 20 percent of uninsured do so (Bloom 1997a). The breakdown by insurance status is similar for working-age adults (Bloom 1997b).
[4] Patients whose choice of hospital is determined largely by proximity may be vulnerable in other, less

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 cancer, 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. The survey data, which provide information on residential location, allow us to 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, not subject to self-reporting bias.

We find that increased distance to the nearest hospital is associated with a lower probability of identifying an emergency room or an outpatient hospital clinic as a usual source of care. It is also associated with an increase in the probability of respondents' reporting a doctor's office as the place they go when sick or in need of health care advice. Distance has little effect on perceived access to care in the population generally, though it

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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).

is negatively related to perceived access for lower-income residents who tend to rely more on hospitals. This effect is partially offset by insurance. Among the elderly, distance is negatively related to the probability of receiving an influenza vaccine. In contrast, we find that hospital closures are associated with an increase in the probability that those with health insurance receive colon cancer screening, possibly reflecting a switch among residents to higher quality hospitals or their increased use of office-based physician care, where referrals for such screening are common.

Increased distance to the nearest hospital is also associated with delays in the receipt of prenatal care and a rise in infant mortality rates, though the latter effect is sensitive to the empirical specification. Finally, we find evidence that increased distance is associated with increased deaths from unintentional injuries and acute myocardial infarction, but not from other causes such as cancer or chronic heart disease, for which timely emergency care is less important.

Data and Methods

Data Sources

We use several independent sources of data. 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.[5]

To examine the effect of distance to the nearest hospital on health outcomes, we use zip code level birth and death reports from California's Department of Health Services. Using the birth data, we assess the impact of distance to the nearest hospital on the receipt of prenatal care and infant mortality rates. The expected effect is theoretically ambiguous. On the one hand, previous studies have been shown maternal health care access, and thus infant health, to be sensitive to distance (Phibbs et al. 2003). Moreover, the time it takes to get to an emergency room may be critical for an infant's recovery from an accident or a serious acute illness occurring after discharge from the hospital. On the other hand, when smaller hospitals with less technically advanced facilities close, more births may occur at larger hospitals with better facilities (e.g., neo-natal intensive care units), which may lead to better birth outcomes.

We use cause-specific mortality data from 1997-2001 to test for an effect of distance to the nearest hospital on mortality 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 count of deaths from heart attacks and unintentional injuries. As a specification check, we also consider the relationship between distance on the number of deaths from colon and lung cancer and chronic ischemic heart disease, outcomes that should be not be sensitive to how long it takes to get to the nearest

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

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 1997-2001 Office of Statewide 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 certain 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.[6]

Econometric Specification

We use a quasi-experimental design to examine how changes in the travel distance from the population center of each 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 for individuals in areas where hospitals closed to 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 annual

[6] LA County residents were affected by 1 opening, a Kaiser facility in Baldwin Park. Because it occurred just prior to the closing of another neighborhood facility, Santa Rosa Hospital, distance from the two affected zip centers to the nearest hospital was virtually unchanged. Moreover, as Kaiser is technically open only to its enrollees, we are understating the true change in distance from the Santa Rosa closing.

[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®.

utilization and mortality data aggregated to the level of the zip code. For both types of data, the general form of the econometric specification is:

$$(1) \qquad Y_{zt} = \alpha Distance_{zt} + X'\beta + \gamma_t + \delta_z + \varepsilon_{zt},$$

where the dependent variable, *Y*, includes the measures of access, utilization and health outcomes just described. Control variables are represented by the vector *X*. In the models estimated using the LACHS data the controls 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]

In the zip code level infant mortality models, the controls include the share of births delivered by race of mother (White, Hispanic, Black, Asian, Filipino, American Indian and unknown), share of births by weight category (under 1500g, 1500-2499g, over 2500g and weight unknown) and share of births by mother's age group (under 20, 20-29, 30-34, 35 and over, and age unknown). When we consider counts of infant deaths (in contrast to infant death rates), we include the total number of births in the zip code as an additional covariate. The models of other mortality counts in a zip code include controls for total deaths, deaths by homicide (to proxy for the general risk of the neighborhood)

[8] Annual unemployment rates are available for 125 cities and "census designated places" 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, which are listed in OSHPD's *Primary Care Clinic Listings*, open and close based on where there is greatest need (US GAO 1995). Thus, we use counts of clinics in an area to proxy for the health care needs and status of a community.

and the age distribution of deaths (to proxy for the age structure of the neighborhood). Both the infant mortality and the mortality count models also control for the number of health clinics in the zip code.

The terms γ_t and δ_z are fixed effects for time (i.e., year) and geographic area. In all of the models we present, we include zip code fixed effects. In these specifications, the effect of distance is identified by changes in mean distance induced by hospital closures. The advantage of this approach is that we can account very completely for differences in demand that may exist across areas due to factors such as the socioeconomic characteristics of the population. In the mortality regressions we also report specifications that include separate time trends for each zip code to account for demographic or economic shifts within a zip code that are not common across areas. Because we have only three years of survey data, however, we do not include zip code-specific time trends in any of the models of individual health care access or use.

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 that replace the zip code dummy variables with city or "community" fixed effects.[9] 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 the analysis.

[9] For areas outside of the city of Los Angeles we use the city as the geographic unit in this specification. Within Los Angeles we include separate fixed effects for distinct communities such as Brentwood, Hollywood, Encino and Boyle Heights. These communities are geographically compact and relatively homogeneous in terms of economic and demographic characteristics.

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, 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 insurance coverage. We also estimate models on a sub-sample of individuals reporting an annual household income of less than $30,000. [10]

All of the outcomes from the LACHS are 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. For these outcomes we estimate probit models. In our analysis of deaths (infant mortality as well as deaths of all residents by cause), we use negative binomial models, exploiting the nonnegative count nature of mortality data while using a more flexible functional form than the more common Poisson model.[11] We do this to avoid introducing additional noise into the analysis, since in many zip code years there are few deaths of any given type.[12] In all models we adjust standard errors to allow for correlation in the error terms at the zip code level.[13]

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[10] Median household income in Los Angeles County in 2000 is roughly $42,000.

[11] The Negative Binomial model is essentially a Poisson regression model with unobserved heterogeneity introduced by a gamma distributed error term. This more flexible functional form allows for over-dispersion. Hausman et al. (1984) pioneered the approach; Long (1997) provides a good review.

[12] For example, in 30 percent of all zip code years there are no infant deaths and in 54 percent there are fewer than 5 deaths from unintentional injuries.

[13] Failure to account for this will cause the precision of our estimates to be overstated, leading to an *over-*

Results

Descriptive Statistics: LACHS

Table 2 presents summary statistics for LACHS respondents overall and separately according to whether they live in zip codes that experienced a change in distance to the closest hospital during the sample period. For the full sample, the average driving distance to the nearest hospital is 2.64 miles. The figures in the second and third columns show that the average distance is greater for individuals who faced an increase in distance due to a closure compared to individuals for whom the distance did not change. This is also true before closures (not shown here): zip codes that experienced hospital closures during this period experienced an increase in driving distance to the nearest hospital by about a mile, from an average driving distance of just under 3 miles to almost 4 miles. Within this group, the change in distance associated with a closure ranged from roughly a tenth of a mile to about 3.6 miles.

Other differences between the two groups suggest the importance of controlling for individual characteristics and area fixed effects. Those who faced a change were significantly more likely to be white (54 vs. 39 percent), U.S. citizens (84 vs. 77 percent), English-speaking (81 vs. 76 percent) and have a college or post-graduate degree (37 vs. 30 percent). Respondents in affected zip codes are also more likely to have private health insurance (58 vs. 51 percent), less likely to have Medi-Cal (4.5 vs. 8.3 percent) and less likely to rely on hospital for care (10 vs. 14 percent). Those affected by closures also have better self-reported health and access to care. These differences are not surprising given that several of the neighborhoods that lost hospitals (e.g. Beverly Hills, Burbank,

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rejection of the hypothesis that changes in distance to the nearest hospital have no effect on access to care (Moulton 1986; Bertrand, Duflo and Mullainathan 2004).

and North Hollywood) are relatively affluent. To the extent that our models do not fully capture this heterogeneity and that the group experiencing a change in distance is "healthier," and of higher SES, we risk understating any negative effects of closure on vulnerable populations.

The last part of Table 2 presents the outcomes we examine. The measures of usual source of care and perceived access are defined for the full sample. In contrast, the questions concerning the receipt of various types of preventive care were targeted to specific relevant populations—e.g., individuals over age 50 for colon cancer screening, individuals over age 65 for flu and pneumonia vaccines and women of different ages for Pap smears and mammograms.

Probit Regression Results: Access to Care and Preventive Screening

The probit regression results for these outcomes are reported in Table 3 (usual source of care and place of care), Table 4 (perceived access) and Table 5 (preventive care). For all models, we report marginal effects (i.e., probability derivatives) computed at the sample means of the data rather than the raw coefficients. Marginal effects of health-related controls are reported in Appendix Tables 1, 2 and 3.[14] In all cases, the "marginal effect" of the interaction between insurance and distance is calculated as the cross-derivative of the standard normal cumulative distribution with respect to distance and insurance, evaluated at the sample means of the data (Ai and Norton 2003).

Panel A of Table 3 looks at whether the respondent has a "particular regular

[14] For sake of brevity, we do not discuss these covariates in the text though they are interesting in their own right. For example, they 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 (primarily seniors), report more difficulty accessing care.

source of care where he/she goes most often." Columns (1) and (3) consider the main distance effect alone; columns (2) and (4) include the interaction between health insurance and distance. In the full sample (columns (1) and (2)), hospital closures have little detectable effect on the probability of reporting a usual source of care. Surprisingly, in the low-income sample, a one-mile increase in distance to the nearest hospital is associated with an almost 2 percent increase in the likelihood of reporting a particular place where care is sought.[15] One possible explanation for this counter-intuitive result is that around the time of a closure, county or city authorities may have increased outreach efforts to encourage low-income patients who had relied on the hospital emergency room (but perhaps did not view it as a "usual" source of care) to find an alternative. Similarly, low-income residents may have responded to the considerable media attention given to hospital closures by identifying an alternative source of care. Finally, some physicians or clinics that serve low-income populations may have seen closures as a business opportunity and either moved into the area or marketed their services more aggressively.

The results in Panels B and C suggest that in the full sample the zero effect on having a usual source of care masks an effect of closures on where patients receive care. Increased distance to the hospital is associated with a decrease in reliance on an ED or clinic when sick (Panel B). Although these effects are not significant at conventional levels, if we exclude patients without a regular source of care (not shown here), the full sample results indicate that a one-mile increase in distance is associated with a statistically significant 1.3 percentage point decline in the probability of reporting an ED or clinic as the source of care (off a base of 17 percent). This reduction coincides with an

[15] The increased likelihood of having a regular place of care appears to be independent of health insurance (see col (4), Panel A) but further analysis using separate interactions for Medi-Cal, Medicare, and "private" insurance (not shown here), suggests that the increase is common to all but Medicare beneficiaries.

increased reliance on a physician's office (Panel C). In both the full and low-income samples, respondents report a 2 to 3 percentage point increase in the likelihood of going to a doctor's office when sick. This effect, which is independent of insurance status, is quite large for the low-income group, suggesting an almost 5 percent increase in reporting that a doctor's office is the usual place of care.[16]

Table 4 takes the analysis a step further by asking how closures and the subsequent shifting of sources of care affect perceived access. Results are given separately for those with (Panel A) and without (Panel B) a regular source of care. Not surprisingly, across all residents, increased distance appears to have little effect on perceived access to care. For low-income respondents, however, a one-mile increase in the distance to the nearest hospital results in a roughly 3 percent decrease in ease of obtaining health care. The effect is fully offset by health insurance, implying that low-income uninsured residents, despite their increase in reporting a doctor's office as their usual source of care, perceive more difficulty in accessing care after a hospital closure. Among low-income residents who report no regular source of care (Panel B) the effect is independent of insurance status and is quite large. A one-mile increase in distance to the hospital is associated with a 7.1 percentage point decline in reported ease of access, which is nearly a 20 percent effect relative to the base of 38 percent. Seniors also report decreased ease of access (not shown here), irrespective of insurance status. Among those 65 and over, a one-mile increase in distance is associated with a 5 percentage point decline in ease of access to care off of a base of 85 percent.

While reported source of care and perceived access are clearly important, we care

[16] This effect is independent of health insurance status, although here again further analysis suggests the increase is common to all (uninsured, privately insured or Medi-Cal insured) but Medicare beneficiaries.

ultimately about the effect of hospital closures on the use of health care services and health outcomes. The regressions reported in Table 5 examine the effect of changes in the distance to the nearest hospital on use of health care services. Panel A considers colon cancer screenings (colonoscopy or sigmoidoscopy) in individuals over 50.[17] In both the full sample and the low-income subsample, the simplest model suggests a negative though insignificant relationship between the probability of screening and increased distance. When we include the insurance interaction, however, we find that for insured individuals there is a *positive* relationship between distance and the probability of screening, although the effect is not statistically significant for the low-income group. For insured people in the full sample, a one-mile increase in distance to the hospital is associated with a roughly 3 percentage point increase in the probability of colon cancer screening or an almost 7.5 percent increase.[18] Since doctors typically provide hospital referrals for this service, the increased screening may be attributable to the increase in regular care sought in a physician's office.

We also estimated the effect of distance on HIV tests for adults under age 65 (Panel B). The coefficients on distance and the interaction between distance and insurance status are all statistically insignificant. When we use an alternative econometric specification, discussed in our sensitivity tests below, however, we find evidence suggesting that hospital closures may decrease the likelihood the residents get

[17] The question was asked of those 40 and older in 1997 but only those 50 and older in subsequent surveys.
[18] The 1997 survey asks about tests in the last two years, whereas later surveys ask whether the respondent has ever had the test. This change creates a bias toward finding a positive effect of distance as the 1997 pre-closure rate of screening in a zip code is by definition less than (or equal to) the lifetime screening rate. Sensitivity tests limiting the sample to the 1999 and 2002 survey years yield results that are remarkably similar for the insured respondents, suggesting a roughly 3 percentage point increase in the probability of a screen with a one-mile increase in distance to the hospital. If anything the results above, understate the negative effect on the uninsured. The results from the 1999-2002 data suggest that the uninsured experience a 5-percentage point decline in colon cancer screens, significant at the 20 percent level.

screened for HIV.

Panel C looks at flu shots in the past year and pneumonia vaccines (ever) for those 65 and over. Because household income is less meaningful for this population, we limit this analysis to the full sample of seniors. A one-mile increase in distance to the hospital lowers the probability of having a flu shot by about 3 percentage points for all seniors. While this result may seem surprising given that flu shots need not be given in a hospital setting, it may reflect the fact that flu shot campaigns are often coordinated by a local hospital. In addition, since hospitals are typically high-volume providers of flu shots, closures may increase congestion at other facilities offering shots and thereby decrease access to the vaccine. In contrast to flu shots, we find no effect of distance on the probability of pneumonia vaccination. The difference between the pneumonia vaccine and flu shot results, however, may be related to the fact that the pneumonia vaccine is given to seniors on a roughly 10-year basis whereas the flu shot is given yearly. Thus, even if seniors are less likely to go to the hospital for a vaccination, this effect may only show up over a long time horizon.

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

Sensitivity Tests

As noted above, by controlling for geographic area effects at such a fine level, we are identifying the impact of hospital closures only as they affect those in the immediate surroundings of the hospital. And, since closures are relatively rare, we capture changes in health of a fairly small percentage of the population. As an alternative specification, we replace the zip code with community or neighborhood fixed effects. 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 to the location of all neighborhood hospitals, not just those that closed during the period of analysis.

Results using this less restrictive model (see Appendix Table 4) are generally quite similar to those with zip code fixed effects. The colon cancer screening results are virtually identical in magnitude but more precisely estimated. In the case of HIV tests, this alternative specification indicates that an additional mile in distance to the nearest hospital is associated with a statistically significant 0.5 percentage point decline in probability of receiving screening. The effect is also negative and of similar magnitude for low-income residents, although only significant at the 19 percent level. In contrast the flu vaccine results are no longer statistically significant when we include neighborhood rather than zip code fixed effects.

Another potential problem with our main analyses is that, as demonstrated by the descriptive statistics in Table 2, people in zip codes not affected by hospital closures are quite different from those in affected zip codes and thus do not necessarily make a good control group. Since those who did experience an increase in distance to the hospital were typically higher SES, however, any bias from the choice of control group is likely to understate deleterious effects of closures and overstate any positive effects.

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 (see Appendix Table 5). Restricting the sample in such a manner cuts the number of observations down by about 85 percent, from about 22,000 to almost 3,000 respondents, and typically, though not always, reduces the precision of the results. In general, however, the results are qualitatively similar. In a few cases, the results suggest that the estimated effects (both positive and negative) using the full sample are understated. The increase in colon cancer screens among insured residents is still statistically significant at the 5 percent level and is about twice the magnitude, suggesting a one-mile increase in distance to the hospital increases the probability of being screened for colon cancer by about 6 percentage points. Similarly, the probability of HIV screening among insured residents declines by 1.8 percentage points, implying a 6 percent reduction in screening that is statistically significant at the 2 percent level. The restricted sample results also suggest that the flu shot estimates from the full sample are understated. The results from the restricted sample imply that a one-mile increase in distance leads to nearly a 10-percentage point decline in testing (a 14 percent effect relative to the sample mean), which is significant at the 10 percent level.

Although the precise magnitude of the results vary somewhat across specifications or samples, the basic qualitative results are clear. On net, the LACHS results suggest both positive and negative effects due to the closure of even poor performing hospitals. Not surprisingly, the negative effects are largely concentrated in vulnerable populations – lower income residents, the uninsured, and seniors.

Zip Code Level Analysis of Prenatal Care and Infant Mortality

We now turn to our analysis of mortality using zip code level administrative data. Table 6 summarizes the data that we use to analyze the effect of hospital closures on receipt of prenatal care and infant mortality. As expected given the LACHS data, mothers in zip codes that faced closures are more likely to be white and less likely to be black or Hispanic. They tend to be older and are also significantly more likely to have received prenatal care in their 1st trimester of pregnancy. The birth weight distribution of their babies is not statistically significant different and the infant death rate is only slightly lower from that of mothers in zip codes that experienced no change in distance to the nearest hospital.

The first two columns of Table 7 consider early use of prenatal care services among women who eventually give birth. With or without zip code time trends, we find a negative effect of increased distance on the share of births that received 1st trimester prenatal care. The effect of distance is larger in the model that includes the zip code trends (-0.658 vs. -0.144), where it is statistically significant at the 6 percent level. However, even this effect is small in economic terms. Relative to the mean of the dependent variable (864), the result in column 2 represents a 0.08% effect.

Next, we examine the effect of distance to the nearest hospital on infant deaths. In columns 3 and 4, the dependent variable is the infant mortality rate (deaths per 1000 live births). Columns 5 and 6 report results from negative binomial regressions in which the dependent variable is the total number of infant deaths; in this specification the total number of births enters on the right hand side. Overall, these models are suggestive of an effect of distance on infant deaths, though the results are sensitive to the specification. In column 3, a one-mile increase in distance to the nearest hospital is associated with a .061 increase in infant deaths per 1000 live births. However, when zip code specific trends are included, the sign on the effect flips and is no longer statistically significant. Similarly, the basic negative binomial model implies that a one-mile increase in distance to the nearest hospital is associated with a roughly 7 percent increase in the number of deaths in the first year of life, but the effect is smaller (4.7%) and not statistically significant (p-value = 0.289) when we add separate time trends for each zip code.

Zip Code Level Analysis of Mortality from Other Causes

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 for the data used in this part of the analysis are reported in Table 8[19] and the key regression results are in Table 9.

For AMI, the basic model indicates that a one-mile increase in distance leads to a nearly a 3% increase in the number of deaths (Table 9, column 1). The magnitude of this effect more than doubles when we include zip code specific time trends (column 2). We obtain similar results for deaths due to unintentional injuries: a one-mile increase in

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[19] Consistent with the differences in SES found in the other data sets, fewer residents in zip codes experiencing a change in distance die by homicide. In contrast, there is no significant difference in the share of total deaths from heart attacks or unintentional injuries.

distance to the nearest hospital is associated with a roughly 4 to 6 percent increase in the number of deaths, with the larger effect coming from the model with the zip code specific time trends.

In contrast, we find no significant relationship between changes in distance to the nearest hospital and deaths from chronic heart disease, colon cancer or lung cancer. Given our LACHS findings of increased colon cancer screenings among those with health insurance and the fact that colon cancer is highly curable if diagnosed and treated early (Tomeo 1999), we may have expected a consequent effect on colon cancer deaths.[20] Since we cannot infer insurance status from death records, however, any effect of early diagnosis on deaths from colon cancer may be masked in our data. Moreover, five years may not provide a long enough time period to see any effect of increased diagnosis (and subsequent treatment) on colon cancer death rates. 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.

Discussion

While important, the finding that hospital closures in Los Angeles County may have reduced access and increased mortality does not necessarily imply that the closures were welfare-reducing. It is necessary to weigh these costs against the benefits of

[20] Unlike diagnostic tests for other forms of cancer or even many other diseases, colon cancer screenings are a "primary prevention" method because early detection of precancerous polyps can prevent the actual development of disease (Tomeo 1999).

closures, most importantly those benefits related to improved operating efficiency and lower costs. While a full cost-benefit analysis of these closures is beyond the scope of this paper, we can conduct a rough assessment.

Scheffler et al. (2001) document that the California hospitals that closed during the period of our study were smaller than average and, prior to closing, had weaker financial performance than those that remained opened. They calculate that statewide these closures reduced total inpatient capacity by between 3 and 4 percent. Shifting care to more efficient hospitals and reducing excess capacity should have reduced system-wide costs. According to Lindrooth et al. (2003), urban hospital closures result in a roughly 3 percent reduction in costs per adjusted admission. Applying this estimate to the average cost per adjusted admission in 1999 in Los Angeles County of $2346 and an annual figure of 5.5 million patient days (OSHPD 2001), implies that the closures in LA County in the late 1990s saved approximately $387 million per year.

Our analysis suggests that the greatest cost of hospital closures is due to the increase in deaths from AMI and unintentional injuries. In our data, the zip code level means for these outcomes are 14 deaths per year for AMI and 5 deaths per year for accidents. Based on our estimates of the effect of a one-mile increase in distance, the mean increase associated with hospital closures in our sample, closures increased AMI deaths an average of 4.5 percent and deaths due to unintentional injuries an average of the 4.85 percent. Together, these estimates translate to an additional 0.873 deaths per year in affected zip codes. Since 35 zip codes were affected, this implies that closures in LA County resulted in an average of 30.5 additional deaths per year. Ignoring the fact that those who die from AMI are typically middle-aged and using standard value of life estimates of between $1 and $5 million (Viscusi 1993), the mortality-related costs of hospital closures may be as high as $92 million, well below the estimated cost savings.

Supplementing this rough cost-benefit calculation with the net costs of reduced HIV testing and influenza vaccinations as well as decreased access to care are unlikely to change this basic assessment. This average calculation, however, masks specific, changes in health care use that may not have been cost-beneficial. For example, consider the effect of closures on flu shots among the elderly, which numerous studies find to be very cost-effective (see Nichol 2003 for an extensive review). One study of elderly members of a health maintenance organization found that influenza vaccines reduced direct medical costs by an average of $73 per person, largely by reducing hospitalizations (Nichol et al. 1998). Our results imply that the hospital closures in LA County resulted in over 26,700 fewer seniors receiving vaccines.[21] Combining these two estimates would imply that the reduced immunizations caused by the closures led to additional medical costs of over $1.8 million. Flu vaccines have also been shown to reduce mortality among the elderly. One meta-analysis cited in Nichol (2003) suggests that vaccinating seniors reduces deaths from all causes by about 50 percent. With about 42,000 deaths per year among seniors in the County and a value of $25,000 per additional year of life lived and 5 more years of life expected, the reduction implies a cost of almost $74 million (42,000 * .50 * .028 * $125,000) in years of life lost.[22]

[21] Specifically, we find that closures reduced the probability of being immunized by 2.8 percentage points. This effect and a total senior population of 955,000 equal 26,740.
[22] Death figures are from http://www.dhs.ca.gov/hisp/chs/OHIR/vssdata/2001data/2001MCountyEX.htm

Conclusions

Past work has shown that urban hospital closures improve the efficiency of the health care systems by shifting care to lower cost facilities (Lindrooth et al. 2003). In a similar vein, we find that hospital closures shift care previously given in emergency rooms and outpatient clinics to doctor's offices, a more appropriate and cost-effective source of regular care (Baker and Baker 1996). Although these efficiency savings from hospital closures are extremely important, they tell only part of the story.

We find that proximity to a hospital is an important determinant of access to care for the more vulnerable residents in Los Angeles County. Lower-income residents and seniors, who tend to rely more on hospitals, report more difficulty accessing care as a result of closures, though this effect is partially offset by insurance. Moreover, increased distance to the hospital lowers the probability that seniors receive flu shots, that younger residents get screened for HIV and the timeliness of prenatal care for pregnant women.

Cause-specific mortality data suggests that urban hospital closures also have implications for the population more generally. We find strong evidence that increased distance to the nearest hospital is associated with higher mortality counts from emergent conditions, such as heart attacks and unintentional injuries. We also find some evidence that distance to the nearest hospital is positively related to infant mortality, though these results are less robust. Overall, we conclude that the costs associated with these adverse outcomes are outweighed by the efficiency gains related to hospital closures. Social welfare may be further increased, however, by promoting low-cost, non-hospital-based ways of treating emergent conditions after a local hospital closure.

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Table 1. Hospital Closures and Openings in the Los Angeles Region: 1998-2002

	Los Angeles County			Neighboring Counties		
Year	Open start of Year	Closed During Year	Opened During Year	Open start of Year	Closed During Year	Opened During Year
1997	133	5	0	89	2	0
1998	128	5	1	87	2	0
1999	124	1	0	85	1	2
2000	123	1	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 nonfederal 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 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.

Table 2. Los Angeles County Health Survey Summary Statistics

	Overall	By Change in Distance to Closest Hospital	
		No Change	Change
Hospital Distance Variables			
Miles to closest hospital (driving)	2.64	2.52	3.48
	(.019)	(.020)	(.049)
Miles to closest hospital (straight line)	1.78	1.67	2.45
	(.012)	(.013)	(.030)
Change in driving distance to hospital	.137	--	1.03
	(.003)		(.015)
Individual Characteristics			
Gender (male)	.407	.407	.408
Age	43	42	43
	(.11)	(.12)	(.27)
Race			
Hispanic	.376	.392	.294
White	.411	.386	.535
Black	.100	.112	.042
Asian	.094	.091	.106
Pacific Islander	.008	.008	.008
American Indian	.005	.007	.007
Other	.003	.004	.005
Citizen	.784	.773	.842
Survey Taken in			
English	.770	.759	.814
Spanish	.200	.213	.141
Mandarin	.010	.009	.015
Cantonese	.006	.006	.005
Korean	.008	.008	.010
Vietnamese	.005	.005	.004

Household Income			
< $10000	.136	.126	.183
$10000-20000	.115	.123	.074
$20000-30000	.179	.187	.134
$30000-40000	.119	.123	.097
$40000-50000	.099	.099	.099
$50000-75000	.080	.080	.080
> $75000	.119	.115	.134
Education Level			
8th Grade or less	.094	.098	.071
9-12th Grade	.102	.108	.072
HS Graduate	.213	.216	.198
Some College	.278	.277	.281
College Grad	.203	.194	.244
Post Grad Degree	.110	.105	.134
Working Status			
Full-Time	.463 (.003)	.462 (.003)	.474 (.008)
Part-Time	.109	.108	.115
Hours Unknown	.005	.005	.006
Not Working	.161	.164	.147
Retired	.127	.127	.131
Homemaker	.095	.096	.094
Marital Status			
Married	.479	.473	.467
Co-habitating	.072	.076	.054
Widowed	.064	.064	.066
Divorced	.100	.100	.099

Separated	.035	.036	.027
Never Married	.250	.252	.240
Household Size	3.09	3.12	2.94
Health Status and Behaviors			
BMI	24.0 (.054)	24.1 (.059)	23.6 (.127)
Self-assessed health: 1=excellent, 5=poor	2.50	2.52	2.37
Diabetes	.063	.063	.062
Arthritis	.173	.174	.168
Heart Disease	.060	.061	.059
Smoke Cigarettes	.160	.162	.154
Health Insurance Status	.521	.508	.588
Insured - Private, Empl, Military	.077	.083	.045
Medi-Cal, non-Medicare	.122	.121	.127
Medicare	.122	.121	.127
Outcome Variables			
Has regular source of care	.781	.779	.792
Source of care is ER or outpatient clinic	.133	.140	.099
Colon Cancer Screen (age>50)	.380	.378	.391
Received HIV Test (age<65)	.358	.367	.312
Flu Shot (age≥65)	.696	.692	.715
Pneumonia Vaccine (age≥65)	.572	.558	.636
# of Observations	23503	20377	3126

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 two years. The flu shot refers to this year while the pneumonia vaccine refers to the respondent's lifetime.

Table 3: Marginal Effect of Distance to the Closest Hospital on Source of Care

	Panel A: Have a Place Where Regular Care is Sought			
Sample	Full		HH Income<30,000	
Driving Distance to Hospital (miles)	.006 (0.93)	.006 (0.88)	.016 (1.78)	.016 (1.41)
Miles * Insurance	--	-.003 (0.48)	--	-.007 (0.86)
Insurance	.241 (35)	.233 (25)	.261 (28)	.253 (19)
Observed Probability	.784	.784	.714	.714
# of Observations	22258	22258	11821	11821

	Panel B: Respondent Goes to a Doctors Office if Care is Needed			
Sample	Full		HH Income<30,000	
Driving Distance to Hospital (miles)	.018 (2.44)	.019 (2.19)	.025 (2.81)	.026 (2.99)
Miles * Insurance	--	-.001 (0.09)	--	.011 (0.34)
Insurance	.358 (39)	.344 (27)	.367 (34)	.348 (22)
Observed Prob.	.619	.619	.486	.486
# of Observations	22481	22481	11990	11990

	Panel C: Respondent Goes to ED or Outpatient Clinic if Care is Needed			
Sample	Full		HH Income<30,000	
Driving Distance to Hospital (miles)	-.008 (1.40)	-.009 (0.54)	-.002 (0.22)	-.003 (0.23)
Miles * Insurance	--	-.010 (0.38)	--	-.005 (0.76)
Insurance	-.048 (9.53)	-.037 (5.96)	-.056 (6.99)	-.041 (3.87)
Observed Prob.	.133	.133	.197	.197
# of Observations	21995	21995	11524	11524

Notes: Standard errors are cluster-adjusted by zip code; absolute value of z-statistics are shown in parenthesis. Regressions include survey year and zip code fixed effects. 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 4. Marginal Effect of Distance to the Closest Hospital on Reported Ease of Access to Health Care Services

	Panel A: All Respondents			
Sample	Full		HH Income<30,000	
Driving Distance to Hospital (miles)	-.000 (0.58)	-.003 (0.61)	-.017 (1.94)	-.016 (1.86)
Miles * Insurance	--	.004 (1.30)	--	.014 (1.83)
Insurance	.296 (40)	.287 (28)	.330 (30)	.309 (20)
Observed Prob.	.716	.716	.605	.605
# of Observations	21848	21848	11532	11532

	Panel B: Respondents Without a Regular Place of Care			
Sample	Full		HH Income<30,000	
Driving Distance (miles) to Hospital	.001 (0.08)	.001 (0.09)	-.071 (2.00)	-.074 (1.90)
Miles * Insurance	--	.008 (1.15)	--	-.001 (0.12)
Insurance	.320 (19)	.303 (13)	.300 (14)	.257 (9.11)
Observed Prob.	.463	.463	.379	.379
# of Observations	4467	4467	3077	3077

Notes: Standard errors are cluster-adjusted by zip code; absolute value of z-statistics are shown in parenthesis. Regressions include survey year and zip code fixed effects. 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 5. Marginal Effect of Distance to the Closest Hospital on Diagnostic Care

	Panel A: Colon Cancer Screening, age≥50			
	Full		HH income<30,000	
Driving Distance (miles) to the Hospital	-.005 (0.45)	-.007 (0.54)	-.003 (0.15)	-.005 (0.22)
Miles * Insurance	--	.033 (2.44)	--	.035 (1.49)
Insurance	.125 (5.55)	.047 (1.44)	.116 (4.63)	.037 (1.05)
Obs Prob	.441	.441	.421	.421
# of Obs	6959	6959	3677	3677

	Panel B: HIV tests, age<65			
Sample	Full Sample		HH Income<30000	
Driving Distance (miles) to the Hospital	.002 (0.21)	.001 (0.20)	.007 (0.80)	.007 (0.81)
Miles * Insurance	--	-.004 (1.16)	--	-.001 (.0.23)
Insurance	.063 (6.82)	.074 (6.27)	.053 (3.95)	.083 (5.45)
Obs. Prob	.360	.360	.390	.390
# of Obs	20105	20105	10430	10430

	Panel C: Preventative Care, age 65+			
	Flu Shot		Pneumonia Vaccine	
Driving Distance (miles) to the Hospital	-.030 (0.67)	-.028 (1.65)	.009 (0.11)	.012 (0.14)
Miles * Insurance	--	-.020 (0.16)	--	-.037 (1.06)
Insurance	.313 (4.65)	.402 (3.89)	.280 (3.84)	.358 (3.39)
Obs Prob	.678	.678	.573	.573
# of Obs	1845	1845	1849	1849

Notes: Standard errors are clustered by zip code; absolute value of z-statistics are shown in parenthesis. All models include zip and year fixed effects and 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), employment status (6), marital status (6), BMI, self-assessed health status, diabetes, arthritis, and whether the respondent smokes.

Table 6: Summary Statistics for Infant Mortality Data: Los Angles County, 1997-2001

	Overall	Distance to Closest Hospital	
	Mean	No Change	Change
Miles to Closest Hospital (driving)	2.81 (.107)	2.77 (.120)	3.09 (.186)
Change in Distance	.054 (.032)	--	.513 (.304)
Driving Time to Closest Hospital (minutes)	6.87 (.148)	6.67 (.147)	8.38 (.605)
# Clinics	.709 (.028)	.744 (.030)	.411 (.055)
Deaths <1 yr per 1000 live births	4.00 (.106)	4.07 (.113)	3.41 (.261)
Neonatal Deaths (<28 days) per 1000 live births	2.73 (.085)	2.77 (.092)	2.35 (.195)
Post-neonatal Deaths per 1000 live births	1.27 (.051)	1.30 (.054)	1.06 (.035)
Share Mothers, White	.333	.318	.465
Share Mothers, Hispanics	.465	.475	.385
Share Mothers, Black	.072	.077	.033
Share Mothers, Asian	.081	.082	.068
Share Mothers, Filipino	.027	.026	.029
Share Mothers under 20	087	.089	.066
Share Mothers 20-29	.455	.458	.427
Share Mothers 30-34	.265	.261	.295
Share Mothers 35 & older	.200	.191	.212
Share weigh<1500g	.012	.012	.011
Share weigh 1500-2499g	.053	.053	.051
Share weigh 2500g +	.935	.934	.937
Prenatal Care in 1st trimester	864	861	893

Per 1000 live births	(1.69)	(1.80)	(4.34)
No prenatal care Per 1000 live births	5.20 (.155)	5.29 (.168)	4.39 (.343)
Zip-year Observations	1673	1498	175

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

Table 7: Effect of Distance to the Closest Hospital and Prenatal Care and Infant Mortality

	1st Trimester Prenatal per 1000 Live Births		Infant Deaths Per 1000 Live Births		Infant Deaths	
Model Type:	OLS		OLS		Negative Binomial	
Driving Distance (miles) to the Hospital	-.144 (0.99)	-.658 (1.91)	.061 (2.24)	-.022 (0.29)	6.56 (2.58)	4.66 (1.06)
Zip Trends	No	Yes	No	Yes	No	Yes
Dep. Var. mean	864	864	4.00	4.00	2.59	2.59
# Observation	1670	1670	1670	1670	1670	1670
Adj R-sq	.300	.287	.300	.287	--	--

Notes: Standard errors are clustered at the zip code level. Absolute value of t-statistics are and shown in parenthesis for the OLS regression and of z-statistics for the negative binomial regression (NBR) models. 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 both the age and racial distribution of mothers, the weight distribution of babies, the number of community health clinics, zip code fixed effects and year fixed effects. Where indicated, zip-code specific time trends are also included. The NBR models also control for total births. (Since the mean of the dependent variable in a binomial 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 $100*[\exp(\beta_k)-1]$.)

Table 8. Summary Statistics for General Mortality Data, 1997-2001

	Overall	Distance to Closest Hospital	
	Mean	No Change	Change
Miles to Closest Hospital (driving)	3.01 (.099)	2.88 (.097)	4.15 (.408)
Driving Time to Closest Hospital (minutes)	6.87 (.148)	6.67 (.147)	8.38 (.605)
Community Health Clinics	.709 (.028)	.744 (.030)	.411 (.055)
Total Deaths	173 (2.97)	176 (3.22)	142 (6.51)
Unintentional Injury Deaths	5.17 (.110)	5.28 (.120)	4.03 (.234)
AMI Deaths	13.9 (2.72)	14.2 (.294)	11.4 (.664)
Chronic Ischemic Heart Disease Deaths	23.7 (.433)	24.1 (.468)	20.4 (1.03)
Lung Cancer Deaths	9.44 (.182)	9.51 (.195)	8.84 (.481)
Colon Cancer Deaths	3.31 (.071)	3.35 (.076)	3.02 (.183)
Homicides	2.96 (.116)	4.08 (.160)	1.12 (.114)
Share Deaths<1 year old	.017	.017	.017
Share Deaths, 1-4 year olds	.004	.003	.004
Share Deaths, 5-14 year olds	.005	.005	.003
Share Deaths, 15-24 years olds	.016	.0161	.018
Share Deaths, 25-34 year olds	.024	.024	.012
Share Deaths, 35-44 year olds	.047	.048	.043
Share Deaths, 45-54 year olds	.078	.078	.076
Share Deaths, 55-64 year olds	.108	.108	.109
Share Deaths, 65-74 year olds	.183	.182	.179

Share Deaths, 75-84 year olds	.272	.270	.286
Share Deaths, 85+ years olds	.246	.247	.244
Zip-year Observations	1675	1500	175

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

Table 9. Conditional Maximum Likelihood Negative Binomial Models: Percentage Change in Deaths Due to a Mile Increase in Distance to the Hospital in Los Angeles County

	AMI		Unintentional Injuries		Chronic Heart Disease		Lung Cancer		Colon Cancer	
Miles	2.93 (1.56)	6.04 (2.37)	3.63 (2.20)	6.14 (2.56)	-0.57 (0.62)	-0.73 (0.34)	1.71 (1.51)	1.87 (1.00)	-2.28 (1.16)	0.24 (0.06)
Zip Trends	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Mean Deaths	14	14	5.3	5.3	24	24	9.4	9.4	3.3	3.3

Notes: Standard errors are clustered at the zip code level; absolute value of z-statistics 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, number of community health clinics, zip code fixed effects and year fixed effects. Where indicated, zip-code specific time trends are also included. (Since the mean of the dependent variable in a binomial 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 $100*[\exp(\beta_k)-1]$.)

Appendix Table 1. Marginal Effects of Health-Related Control Variables from Baseline Models of Regular Source of Care (Table 3)

	Regular Care		Care in doctor's Office		Care in ED or Clinic	
Sample	Full	Income< 30,000	Full	Income< 30,000	Full	Income< 30,000
Distance (miles)	.006 (0.93)	.016 (1.78)	.018 (2.44)	.025 (2.81)	-.008 (1.40)	-.002 (0.22)
Insurance	.241 (35)	.261 (28)	.358 (39)	.367 (34)	-.048 (9.53)	-.056 (6.99)
BMI	.002 (4.28)	.002 (2.81)	.003 (5.71)	.003 (4.90)	.000 (0.03)	-.000 (0.60)
Self-assessed Health Status	.001 (0.39)	.000 (0.04)	-.014 (5.71)	-.023 (4.55)	.010 (4.28)	.015 (3.71)
Diabetes	.071 (6.00)	.092 (5.08)	.037 (2.36)	.036 (1.73)	.027 (3.35)	.050 (3.64)
Arthritis	.032 (3.59)	.037 (2.61)	.020 (1.93)	.024 (1.56)	.006 (1.02)	-.002 (0.17)
Smoke Cigarettes	-.016 (2.16)	-.027 (2.15)	-.017 (1.68)	-.016 (1.04)	-.000 (0.05)	-.000 (0.04)
Observed Prob	.784	.714	.619	.486	.133	.197
Observations	22258	11821	22481	11990	21995	11524

See notes to Table 3.

Appendix Table 2. Marginal Effect of Health-Related Control Variables from Baseline Models of Ease of Access to Health Care Services (Table 4)

	All Respondents		Respondents Without a Regular Place of Care	
Sample	Full	HH Income<30,000	Full	HH Income<30,000
Driving Distance to Hospital (miles)	-.000 (0.58)	-.017 (1.94)	.001 (0.08)	-.071 (2.00)
Insurance	.296 (40)	.330 (30)	.320 (19)	.300 (14)
BMI	.001 (1.93)	.001 (2.08)	.003 (2.16)	.002 (1.93)
Self-assessed Health Status	-.045 (15)	-.056 (12)	-.063 (7.24)	-.059 (6.07)
Diabetes	.008 (0.59)	.028 (1.53)	.068 (1.24)	-.044 (0.72)
Arthritis	-.027 (2.71)	-.045 (2.93)	-.047 (1.27)	-.050 (1.23)
Smoke Cigarettes	-.023 (2.53)	.002 (0.17)	-.011 (0.46)	.024 (0.92)
Observed Prob.	.716	.605	.463	.379
# of Observations	21848	11532	4467	3077

See notes to Table 4.

Appendix Table 3. Marginal Effects of Health-Related Control Variables from Baseline Models of Diagnostic and Preventative Care (Table 5)

	Colon Cancer Screen		HIV tests		Vaccinations	
	Full Sample	Income< 30,000	Full Sample	Income< 30,000	Flu Shots, age≥65	Pneumonia, age≥65
Distance (miles)	-.005 (0.45)	-.003 (0.15)	.002 (0.21)	.007 (0.80)	-.030 (0.67)	.009 (0.11)
Insurance	.125 (5.55)	.116 (4.63)	.063 (6.82)	.053 (3.95)	.313 (4.65)	.280 (3.84)
BMI	.003 (2.47)	.001 (1.06)	-.001 (1.20)	.000 (0.03)	-.003 (1.19)	.004 (1.48)
Self-assessed Health Status	.013 (1.98)	.021 (2.35)	-.005 (1.29)	-.010 (1.98)	.014 (1.09)	.014 (0.88)
Diabetes	-.007 (0.32)	.016 (0.61)	.048 (2.76)	.058 (2.47)	.104 (3.10)	.037 (0.90)
Arthritis	.087 (5.72)	.071 (3.41)	.024 (2.07)	.014 (0.82)	.092 (3.42)	.104 (3.52)
Smoke Cigarettes	-.111 (6.13)	-.093 (3.47)	.030 (2.93)	.047 (3.39)	-.201 (4.17)	-.148 (3.04)
Observed Prob	.441	.421	.360	.390	.678	.573
Observations	6959	3677	20105	10430	1845	1849

See notes to Table 5.

Appendix Table 4. Sensitivity Test: Neighborhood Fixed Effects

	Colon Cancer Screens, age≥50			
Sample	Full Sample		HH Income<30000	
Driving Distance to the Hospital (miles)	.001 (0.49)	-.000 (0.20)	-.002 (0.45)	-.005 (0.94)
Miles * Insurance	--	.031 (2.96)	--	.031 (2.08)
# of Obs.	6934	6934	3682	3682
Obs. Prob.	.440	.440	.411	.411

	HIV tests, age<65			
Sample	Full Sample		HH Income<30000	
Driving Distance to the Hospital (miles)	-.004 (1.63)	-.004 (1.35)	-.006 (1.30)	-.005 (1.13)
Miles * Insurance	--	-.005 (1.84)	--	-.003 (0.63)
# of Obs.	20067	20067	10364	10364
Obs. Prob.	.360	.360	.391	.391

	Flu Shots, age≥65		Pneumonia Vaccine, age≥65	
Driving Distance to the Hospital	-.004 (0.54)	-.003 (0.44)	-.002 (0.25)	-.002 (0.22)
Miles * Insurance	--	-.037 (1.24)	--	-.016 (0.65)
# of Obs	1887	1887	1867	1867
Obs. Prob	.695	.695	.571	.571

Notes: All regressions include neighborhood fixed effects. For all other details see notes to Table 5.

Appendix Table 5. Sensitivity Test: Zip Codes Experiencing Changes in Distance to the Nearest Hospital

	Colon Cancer Screens, age≥50		HIV Tests, age<65	
Driving Distance to the Hospital	-.015 (1.12)	-.017 (1.02)	.002 (0.32)	.000 (0.01)
Miles * Insurance		.064 (2.08)		-.018 (2.37)
# of Obs	982	982	2647	2647
Obs. Prob	.456	.456	.308	.308

	Flu Shots, age≥65	Pneumonia Vaccine, age≥65
Driving Distance to the Hospital	-.098 (1.63)	.030 (0.43)
# of Obs	238	226
Obs. Prob	.710	.677

See notes to table 5.