The Marginal Benefit of Hospitals: Evidence from the Effect of Entry and Exit on Utilization and Mortality Rates

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Abstract

Whether policies that change health care consumption affect health depends on the marginal benefit of the affected health care. I use variation in access to hospitals caused by nearly 1,300 hospital entries and exits to show that hospital entries cause sharp increases and exits cause sharp decreases in the quantity of inpatient care and emergency department visits with no short-term effect on the mortality rate. Thus, preventing hospital exit is not a cost effective way to save lives on average. However, exits of some hospitals with larger impacts on access to care increase the mortality rate and produce lower cost per life saved estimates.

JEL: H51, I11, L84

Keywords: hospital entry, hospital exit, utilization, mortality, cost-per-life-saved

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1 Introduction

Some have argued that a substantial amount of health care does not benefit patients, and thus people regularly receive services for which the social marginal cost exceeds the marginal benefit (Berwick and Hackbarth 2012, Cutler 2014, and Schwartz et al. 2014). However, some health care services clearly pass this cost-benefit test, and policies that reduce care on the wrong margins could be harmful. US hospitals are both a source of significant health care spending, over $1 trillion annually, and life-saving health care.[1] Reduced access to hospitals could generate substantial savings without affecting patient health if the care provided by marginal hospitals is sufficiently low-value or cause significant harm if the care provided by marginal hospitals is high-value.

Estimates of the benefit of marginal hospitals are needed to evaluate policies that affect access to hospitals. For example, since 1997 Medicare has paid rural Critical Access Hospitals higher rates to prevent them from exiting at a cost of around $2 billion dollars a year (Gowrisankaran et al. 2017 and MedPAC 2012). Concerns about health care access have also motivated protests over hospital exits including a North Carolina mayor who walked to Washington, DC following the death of one of his constituents after the local hospital exited.[2] On the other hand, 35 states have certificate of need laws that could limit hospital entry and reduce health care spending.[3] Whether such policies are beneficial depends in part on whether hospital entry and exit affects mortality rates and at what cost. There is little evidence of the number of lives saved per dollar spent at this margin. This lack of evidence is in part because precise estimates require large numbers of entries and exits and an identification strategy that accounts for endogenous hospital entry and exit.

In this paper, I evaluate one dimension of this cost-benefit trade-off - the effect of hospital entry and exit on health care utilization and mortality rates. I estimate the effect of entering and exiting hospitals on hospital costs, measures of utilization like hospital admissions and ER visits, and mortality rates using a difference-in-differences design and nearly $1,300$ general hospital entries and exits during the 1982-2010 time period. The large number of events allows for precise estimates of the effect of hospitals on the margin of exiting on mortality rates in their communities. The long sample period and detailed data also allow me to check for pre-trends and construct placebo tests to show the estimates are plausibly causal.

I quantify this dimension of the cost-benefit analysis using the number of lives saved per unit of health care. It is the ratio of the change in the mortality rate in an area following a hospital entry or exit to the change in hospital operational costs or admissions caused by an entry or exit. This ratio is a parameter that is useful for informing policies that seek to prevent hospital exit and restrict hospital entry. However, it does not measure the full benefit of entering or exiting hospitals

[1] See, NCHS 2017, and e.g., Doyle et al. (2015).

[2] Mackey (2015). For additional examples see the online appendix.

[3] CON-Certificate of Need State Laws, *National Conference of State Legislatures*, 12/20/2021

because these events could affect health without affecting mortality rates and have other benefits and costs that I discuss in section 6.

I find that both hospital entry and exit cause an immediate, persistent change in the amount of hospital-based health care people receive. Exits reduce the total cost of operating all hospitals in their health service area by a statistically significant $30 per person while entries increase costs by a marginally significant $52 per person. There are substantial effects on the extensive margin of hospital care. Following an exit the number of admissions fall by 1.0 per 1,000 people and ER visits fall by 4.9 per 1,000 people, i.e., about 0.8 percent of the admissions and 1.5 percent of ER visits in each health service area.

Despite significant effects on the quantity of care, I find hospital entry and exit have no immediate effect on the all-cause mortality rate in the county and evidence that exit *reduces* all-cause mortality in the long-term. The mortality estimates paired with the substantial reduction in health care costs and utilization suggest the cost-per-life-saved from preventing hospital exit is high on average. I can reject that the number lives saved per million dollars spent at exiting hospitals is greater than 0.05, which is about $20 million per life saved. However, this high cost-per-life-saved is driven by hospitals with readily available alternatives. Exits with larger impacts on access to care cause mortality rates in the county to increase significantly in some specifications, and have cost-per life saved estimates in the $1.9 to $2.9 million range. There is also evidence that the average exit causes harm to some patients via statistically significantly higher AMI (heart attack) and kidney disease mortality among people living in the hospital's county.

The high cost-per-life-saved and long-term decrease in mortality in counties following exit is driven by exits in places where people can switch to nearby alternative hospitals and who may still be able to quickly access care in an emergency. Consistent with this interpretation, the effect of exit on inpatient utilization is the smallest for people whose next closest hospital is nearby. Additionally, I show that the potential harm from exit is mitigated to some degree because it does not affect admissions for the most severe diagnoses and it causes patients to be admitted to higher quality hospitals measured using risk-adjusted mortality rates following AMI admissions.

The null effects I estimate for admissions for diagnoses that are severe or not deferrable (e.g., hip fracture admissions or births), suggest my estimates are not biased by shocks that coincide with hospital entry/exit and that affect both deferrable and non-deferrable conditions. These estimates effectively serve as placebo tests. In addition, most plots of the leads of hospital entry/exit show no evidence of pre-trends that would indicate the estimates are biased by changes in demand for care that precede the entry or exit event.

My paper is most closely related to work that has looked at the effect of hospital exits on both health care utilization and mortality rates. Joynt et al. (2015) found that 195 hospital exits from 2003-2011 did not significantly affect the amount of inpatient care Medicare beneficiaries' received

or the probability they died during the two years following an exit. However, their confidence intervals included changes in the mortality rate and the quantity of care of a sufficient size that we cannot draw firm conclusions about the benefit or harm of hospital exits. Subsequent work by Carroll (2019) focused on rural hospitals that are small enough to be eligible for the Critical Access Hospital program. She found that exits reduced utilization of hospital care and increased mortality for Medicare patients admitted to the hospital for time-sensitive conditions with a cost to Medicare per quality-adjusted life-year saved of $16,000.[4]

My paper expands the focus of study to hospital entries and exits in both urban and rural areas, small and large hospitals, and to all patients rather than only Medicare patients. It has a sufficient number of events to reject that preventing the average exiting hospital from closing is a cost effective way to save lives. In addition, I contribute to the literature by showing there is substantial heterogeneity in the effects of hospitals on the margin of exiting depending on the availability of alternatives and by providing evidence for why this heterogeneity exists.

The literature on the incremental benefit of health care largely estimates the benefit along the intensive margin, i.e., conditional on receiving treatment at a hospital (Almond et al. 2010, Almond et al. 2011, Almond and Doyle 2011, Doyle 2011, and Doyle et al. 2015, Doyle et al. 2017, Jena et al. 2014, and Silver 2021), although studies of the effect of health insurance status on health can be interpreted as measuring the marginal return on care on a combination of the intensive and extensive margins (e.g., Doyle 2005 and Sommers et al. 2012). Many, but not all, of the studies focused on the intensive margin have found that higher quantities of treatment improve survival rates. My paper contributes to this literature by providing estimates of the cost of saving lives along a different, policy relevant margin. My estimates may differ from this literature because my results suggest that patients who are at the margin of being admitted to the hospital have less severe conditions than some inframarginal patients, particularly when there is another hospital nearby, and I find evidence that exits shift inframarginal patients to higher quality hospitals.

My estimates on the quantity of inpatient care and AMI mortality in counties point in the same direction as papers that have estimated the effect of changes the number of hospitals or ERs on each of these outcomes individually. My quantity estimates are consistent with the Chung et al. (2017) result that hospital entry due to hospital construction subsidies in the 1948-1975 period increased admissions in counties, and the Garthwaite et al. (2018) finding that hospital exits in the 1987-2000 period reduced hospital revenue in commuting zones but not spending on uncompensated care. I also find evidence that hospital exit increases AMI mortality which is consistent with estimates of the effect of emergency department closures on AMI mortality in the US (Shen and Hsia 2016), the effect of hospital closures in LA County on AMI mortality and accidental deaths (Buchmueller

[4] An early study focused on 11 rural hospital exits found significant reductions in inpatient care received by Medicare patients, and large, statistically insignificant increases in mortality (Rosenbach and Dayoff 1995).

et al. 2006), and hospital closures in Sweden on AMI mortality (Avdic 2016).

2 Data

2.1 Health Care Utilization, Hospital Quality, and Health

My primary source of health care utilization is hospital-level data from the American Hospital Association (AHA) annual survey from 1982-2010. The AHA data has detailed information on health care utilization and hospital operating costs that reflect the resource costs of running a hospital, the denominator in my lives saved per unit of health care calculation. I use the AHA data to measure the effect of entry/exit on hospital costs, admissions, inpatient days, and other services offered by hospitals including the number of ER visits and births. I supplement this data with hospital revenue, costs, admissions, and inpatient days for a shorter period (1999-2010) from the Medicare Cost Reports.

I aggregate the data to geographic areas called health service areas that are groups of counties that are "relatively self-contained with respect to the provision of routine hospital care" (Makuc et al. 1991),[5] in order to measure the effect of entry/exit in areas large enough that few people are likely to leave the area to receive care but not so large that a very small percentage of people living in the area would be affected by an entry/exit. Health service areas are similar in size to the commuting zones used by Garthwaite et al. (2018) to study the effect of hospital exit on uncompensated care with AHA data.[6] Health service areas are also about 4.25 times larger than the Dartmouth Atlas hospital service areas which are defined using zip codes and are also designed to capture areas where Medicare patients receive hospital care. I use health service areas rather than Dartmouth Atlas defined areas because my key source of mortality data is available by county but not zip code, so it maps to health service areas (groups of counties) but not hospital service areas (groups of zip codes).

I estimate the effect of entry and exit on mortality using the mortality rate from the Compressed Mortality File from 1982-2010.[7] It includes the total mortality rate, diagnosis codes that I use to construct health care amenable mortality rates following Borgschulte and Vogler (2020), AMI mortality rates, and mortality rates for additional causes of death. Total mortality is the numerator in the lives saved per unit of health care. I analyze these data at the bin-level using bins defined by county of residence, gender, race, and age groups, and report the mortality results in deaths per

[5]Health service areas are assigned to the state where a plurality of their population resides. Rural health service areas have urban populations of under 20,000 in each county in 1995 and do not border metropolitan areas.

[6]Health service areas are roughly 92% as large as the commuting zones in Garthwaite et al. (2018).

[7]National Center for Health Statistics, Compressed Mortality File 1968-1988, and National Center for Health Statistics, Compressed Mortality File, 1999-2014.

100,000 individuals.[8] I use the bin-level data rather than aggregating the data to the health service area-level, like the AHA data, because it allow for a more detailed set of controls, i.e., bin fixed effects, and it allow for analysis of the effect of entry/exit in smaller areas where the event is more likely to affect mortality. The mortality rate is reported by county of residence so the data do not need to be aggregated above the county-level to account for people traveling between counties to receive care.

I supplement these data sources with Medicare data that contains individual and claim-level measures of the quantity of all types of health care billed to Medicare from 1999-2011, mortality data from 1999-2011, and mortality by cause of death from 1999-2008. Although the Medicare data is available for a shorter time period than my other data sources, and it only includes people with traditional Medicare, it is much more detailed than the other data sources. I use it to estimate effects of entry/exit on outpatient care, the severity of the marginal patients' diagnoses, and to construct measures of hospital quality. I measure diagnosis severity using the Charlson Co-Morbidity Index, the average in-hospital mortality rate for each primary diagnosis, and by diagnosis. I measure hospital quality using risk adjusted in-hospital mortality following AMI and heart failure admissions using AHRQ's approach. I supplement the quality measures constructed from Medicare claims data with a broader set of summary measures of hospital quality from CMS including risk-adjusted readmission rates of admitted patients, risk-adjusted mortality rates of admitted patients, and patient satisfaction at individual hospitals in CMS's Hospital Compare database for approximately 2007-2016.[9]

I aggregate the individual Medicare data to bins defined by beneficiary birth cohort, race, sex, zip code of residence, county of residence, and year. These bins are finer than the bins reported by the Compressed Mortality File and allow analyses using the patient's zip code of residence. I use the zip code of residence to measure the effect of an entry/exit near a beneficiary or that changes the distance to the closest hospital on all health care that Medicare pays for regardless of location. This approach allows the analysis to focus on beneficiaries that are likely to be affected by the entry/exit and produce estimates of the effect of hospital entry/exit on health care utilization that are not affected by patients leaving an area to receive care. After excluding beneficiaries who are likely to have incomplete data, the final Medicare data set includes 318 million beneficiary-years.[10] The aggregated data set has 5 million bins and 36 million bin-years.

[8] I define race as white, black, other, and age using 13 age groups.

[9] I construct a measure of each hospital's average quality adjusted for time-trends by regressing the quality measure on year fixed, computing the residuals, adding back the constant (typically the 2007-2009 mean), and then computing the average across these years.

[10] In each year, I exclude beneficiaries living outside the 50 states and DC, who are enrolled in the Medicare HMO, who are not enrolled in Medicare part A or part B, who are older than 100 or younger than 66, and who have zip codes or county codes that cannot be merged with hospital service areas or health service areas. I also winsorized all non-binary, non-diagnosis specific, Medicare outcomes are to the 1st and 99th percentiles.

In all data sets the expenditure measures are inflated to 2012 dollars using the CPI for hospital and related services. For readability of the tables and consistency with the literature, expenditure variables are analyzed in per capita units, all other measures of utilization are analyzed in per 1,000 people units, and mortality is measured as deaths per 100,000 people. Distance is measured as the spherical distance between zip codes or points defined using latitude and longitude.

2.2 Hospital Entry and Exit Data and Additional Controls

The main source of hospital entries and exits is the AHA's Summary of Hospitals for the 1983-2011 time period. The independent variables I focus on are the net change in the number of hospitals in a geographic area due to entry or exit. The AHA's Summary of Hospitals distinguishes when a hospital joins or leaves the AHA data due to entry and exit from when a hospital joins or leaves the AHA data due to a merger and demerger. I only use changes in the number of hospitals due to entry and exit. I treat conversions from and to non-hospital medical facilities, for example, nursing homes, as entries and exits.

In the non-Medicare analyses, I focus on the 109 (out of 494) entrants that report they are open less than a year because this subset of entrants better matches the timing of hospital entry/exit in the Medicare data (online appendix figure 1), and I use all 1,185 exits. In the analysis of the Medicare data I use all entry/exit events and recode them to match the timing of entry/exit in the Medicare data. I have 191 entries and 275 exits during the Medicare sample period. I also show my results are robust to the source of exit data using a sample of exits from Garthwaite et al. (2018) for the 1987-2000 period compiled from Office of the Inspector General reports.

I control for changes in demand for health care using annual data from the decennial census, intercensal population estimates, and county business patterns. The AHA data do not include detailed population information so I control for changes in the population in the health service area using the US Census Bureau data to construct 36 population variables defined by gender, race (white or non-white), and age (10-year age groups from 0 to 80 and 80+). In the Compressed Mortality File and the Medicare data I control for the population demographics using demographic group fixed effects. The county business patterns data combined with the census data provide controls for the level of economic activity in a county or health service area including establishments per capita, nominal payroll per employee, and the employment to population ratio, which are included in the main specifications.

3 Characteristics of Entering and Exiting Hospitals

The number of independently reporting short-term, general hospitals in the AHA data decreased from $5,994$ in 1980 to $4,756$ in 2011 with an even larger percentage decrease in the number of beds. Net exit caused about half of the decrease, and the remainder was due to mergers that caused the AHA to combine multiple independently reporting hospitals into fewer records. Inpatient days also fell which Cutler (2014) argues was caused by changes in insurance reimbursement policy and perhaps advances in medical treatment.

Entering and exiting hospitals appear to be qualitatively different than other hospitals and to differ from each other in some ways. Entering and exiting hospitals tend to be smaller and treat fewer patients than hospitals that never enter or exit (online appendix table 1) and also differ from other hospitals in their area. The top panel of table 1 shows results from regressions in a hospital-year level data set of hospital characteristics on an indicator for the year a hospital enters, a year before a hospital exits, and health service area-year fixed effects. The regressions show that both entering and exiting hospitals are small relative to hospitals in their health service areas, they have lower capacity utilization, and they cost more to operate per patient. Exiting hospitals are much less likely to offer high acuity services, measured by having an ICU, but this is not true of entering hospitals.[11]

There is limited public data on hospital quality until the 2000s so I use CMS's Hospital Compare data to compare entering and exiting hospital quality near the end of the sample period. The middle and bottom panels of table 1 show results from cross-sectional regressions of average hospital quality on indicators for if the hospital entered or exited in the 2005-2010 time period, and health service area fixed effects. Readmission rates are slightly lower at entering hospitals and higher at exiting hospitals than other hospitals in their health service areas for two of the three outcomes, but the differences are not statistically significant and are small in magnitude. Patient satisfaction is significantly higher at entering hospitals and lower at exiting hospitals than other hospitals in their health service areas. Patients admitted to entering hospitals have significantly lower risk-adjusted heart failure and pneumonia mortality rates, but not risk-adjusted AMI mortality rates than other hospitals, with magnitudes of about 3-5 percent. Patients admitted to exiting hospitals have marginally significantly higher risk-adjusted AMI mortality rate and pneumonia mortality rates of about 2 and 5 percent, respectively. Risk adjusted-heart failure mortality rates are also slightly higher at exiting hospitals but the difference is not statistically significant.

These results suggest that entering hospitals have higher measured quality than other hospitals and exiting hospitals have lower measured quality than other hospitals with magnitudes that are

[11] Similarly, Cilberto and Lindrooth (2007) showed that from 1988 to 1997 exiting hospitals were less efficient, had lower revenue per patient, had fewer beds, were more likely to be for-profit, and were less likely to offer "high-tech" services than other hospitals in their region.

not large. These findings are in line with Chandra et al. (2016) who show that the combination of hospital entry and expansion of low volume service lines reduced risk-adjusted AMI, heart failure, and pneumonia mortality rates of admitted patients, while the combination of hospital exit and cuts in low volume services lines reduced risk-adjusted AMI and increased heart failure mortality by a small amount.

Entering and exiting hospitals are also on very different utilization trajectories. Regressions using a hospital-year level data set of admissions on leads of exit or lags of entry, controlling for health service area-year fixed effects, show that exiting hospitals' admissions are declining relative the other hospitals in their health service areas prior to exit, while entering hospitals' admissions rise for several years following entry (online appendix figure 2). Despite these trends, there are still sharp changes in the number of patients they treat in the year of entry or exit, which is the variation my identification strategy exploits. In addition, I show later there are no pre-trends in utilization per capita at the health service area-level for most outcomes.

These results suggest that shutting down a hospital on the margin of exiting could have different effects than closing inframarginal hospitals, and that entering and exiting hospitals could have asymmetric effects on patient health outcomes because of differences in quality of each of these types of hospitals.

4 Empirical Strategy

4.1 Empirical Model

I estimate the number of lives saved per unit of health care using the ratio of the estimated effect of entry or exit on mortality in an area to the effect of entry or exit on the quantity of care. I estimate the effects separately for health care utilization and mortality because both outcomes are individually important, and the unit of observation and available controls differ across the main quantity and health data sets. My primary source of quantity data is only available at the hospital level and must be aggregated to a relatively large geographic area in order to estimate the effect of entry/exit, and thus it uses health service area-level controls. While the Compressed Mortality File and the Medicare data are available by county or zip code of residence and demographic group, which allows for demographic group fixed effects and county-level controls.

4.1.1 Estimates using AHA Data

In the empirical model the dependent variables, y_{at}, are measures of the quantity of hospital treatment like the number of admissions, inpatient days, or ER visits per 1,000 people or hospital costs

per capita in year, t, and in a health service area, a.[12] They are a linear function of the number of hospitals, h_{at}; other observables including a vector of demographic characteristics and measures of economic activity described in section 2.2, $\mathbf{x}_{at}$; state-year fixed effects (the interaction of state and year fixed effects), γ_{st}; health service area fixed effects, ρ_a; health service area trends (a linear time trend interacted with health service area fixed effects), $t\rho_a$; and an error term assumed to be orthogonal to the regressors, ε_{at}.[13]

$$y_{at} = \beta h_{at} + \delta \mathbf{x}_{at} + \gamma_{st} + \rho_a + t\rho_a + \varepsilon_{at} \tag{1}$$

I focus on the effect of changes in the number of hospitals due to entry and exit. I exclude mergers from the independent variable of interest by estimating the model in first differences and measuring the change in the number of hospitals, Δh_{at}, as the number of entrants minus the number of exiting hospitals. I include the lag of net hospital entry, Δh_{at-1} in the model because hospitals do not all open or close at the beginning of each year. When hospitals open later in the year, part of the measured effect of the entry or exit will spill over into the subsequent year and the lag term is needed to capture it. If the effect of the event is immediate and permanent, the first difference specification with one lag will capture both the short and long-term effect of net entry. The first differencing eliminates the health service area fixed effect in equation (1) and means the ρ_a term in equation (2) should be interpreted as a health service area specific time trend because $t\rho_a - (t-1)\rho_a = \rho_a$. The baseline first difference model is

$$\Delta y_{at} = \beta_0 \Delta h_{at} + \beta_1 \Delta h_{at-1} + \delta \Delta \mathbf{x}_{at} + \gamma_{st} + \rho_a + \varepsilon_{at} \tag{2}$$

Both equations (1) and (2) assume that entries and exits have symmetric effects on the outcome variables and the outcomes are affected by the net of hospital entry and exit, not the number of individual entries or exits. A positive $\hat{\beta}_0$ and $\hat{\beta}_1$ would indicate that hospital entry causes increases in the outcome variable, while hospital exit reduces it. Most specifications in the paper allow for asymmetry in the effect of net entry and net exit, where N^{entry} is the number of net entrants and where N^{exit} is the number of net exits.[14] By focusing on net entry and net exit, rather than the number entries and number of exits, I allow entries and exits have different effects depending on whether an area is gaining or losing hospitals. However, this requires assuming there is symmetry in the effect of entry and exit in the 10 of 992 health service area-years with net exit and simultaneous entry (there are no instances of net entry with a simultaneous exit). This approach does not exploit the 14 health service area-years with exactly the same number of entries and exits. I show

[12] I draw on Gentzkow, Shapiro, and Sinkinson's (2011) model and discussion of the bias of the estimates of the effect of entry and exit of firms on an outcome using a difference-in-differences estimator.

[13] The regression models are estimated using reghdfe (Correia 2016).

[14] $N_{at}^{entry} = 1[\Delta h_{at} > 0]|\Delta h_{at}|$ and $N_{at}^{exit} = 1[\Delta h_{at} < 0]|\Delta h_{at}|$

in Section 5.3, this specification is consistent with the results of a more flexible model. The main specification is then

$$\Delta y_{at} = \beta_0^{entry} N_{at}^{entry} + \beta_1^{entry} N_{at-1}^{entry} + \beta_0^{exit} N_{at}^{exit} + \beta_1^{exit} N_{at-1}^{exit} + \delta \Delta \mathbf{x}_{at} + \gamma_{st} + \rho_a + \varepsilon_{at} \tag{3}$$

I report the sum of the entry and exit coefficients, i.e., $\beta^{entry} = \beta_0^{entry} + \beta_1^{entry}$ and $\beta^{exit} = \beta_0^{exit} + \beta_1^{exit}$, which are the full effect of the entry and exit. This model estimates whether a hospital exiting or entering a health service area affects the amount of health care people receive relative to other areas in a state-year that are not experiencing exit or entry controlling for changes in the demographics and economic activity in the health service area and a linear trend in the health service area. All models are estimated with population weighted OLS (clustered at the health service area-level) when the outcome is in per-person units so the estimate can be interpreted as the effect of entry/exit on the average affected person. I exclude the time trend from sub-samples with short panels.

4.1.2 Estimates using Bin-Level Data

The Compressed Mortality File and the Medicare data are available at lower levels of aggregation than the AHA data. I take advantage of this additional information by analyzing these data at the bin-level and controlling for demographic group-area fixed effects. I analyze the Compressed Mortality File at the race-sex-age group-county of residence-year level, which is the original level of aggregation of that data set after combining a few small demographic groups. The Medicare data is more detailed and allows me to analyze the data using finer bins. I aggregate the data to the birth cohort-race-sex-zip code of residence-county of residence-year level. This approach has two key advantages relative to aggregating the data to the health service area-level and running specifications that exactly parallel the analysis of the AHA data. First, it allows for the effects of entry and exit to be identified off of changes in the number of hospitals in an area within a demographic group. Second, it focuses the analysis on populations that are on average nearer to the entering or exiting hospital and thus more likely to be affected by the entry or exit. Both changes are important for detecting the likely small effects on mortality rates.

In the main mortality specifications, I estimate the effect of entry/exit in health service areas, N_{at}^{entry} and N_{at}^{exit}, to match the unit of entry/exit in the AHA data and in counties, N_{ct}^{entry} and N_{ct}^{exit}, because I expect the model to be more likely to detect an effect of entry/exit for people who live nearer to the entering/exiting hospital. The shorter Medicare sample only includes a subset of the population and experiences many fewer entries/exits, which absent changes to the specification would tend to reduce the power to detect effects. However, this sample allows the analysis to focus

on people likely to be most affected by the event. To that end, the primary Medicare analyses use the number of entries and exits that change the distance to the nearest hospital, N_{dt}^{entry} and N_{dt}^{exit}, which means the entry of a hospital that is closer to the beneficiary than any incumbent hospital and the exit of the beneficiary's closest hospital.

To simplify notation, I index the mortality and Medicare bins using b. The outcome variables, y_{bt}, include the mortality rate from both the Compressed Mortality File and the Medicare data and measures of the quantity of care and quality of care in the Medicare data. Like for the AHA data, I use a first difference model with economic activity related controls described in section 2.2, $\mathbf{k}_{ct}$ and state-year fixed effects, γ_{st}. The first difference removes the bin fixed effects, but this model is still identified off of within bin variation. Equations (4) and (5) are used to estimate the effect of hospital entry/exit with the Compressed Mortality File in a demographic group's county of residence, c, and health service area of residence, a, respectively.

$$\Delta y_{bt} = \beta_0^{entry} N_{ct}^{entry} + \beta_1^{entry} N_{ct-1}^{entry} + \beta_0^{exit} N_{ct}^{exit} + \beta_1^{exit} N_{ct-1}^{exit} + \delta \Delta \mathbf{k}_{ct} + \gamma_{st} + \varepsilon_{bt} \tag{4}$$

$$\Delta y_{bt} = \beta_0^{entry} N_{at}^{entry} + \beta_1^{entry} N_{at-1}^{entry} + \beta_0^{exit} N_{at}^{exit} + \beta_1^{exit} N_{at-1}^{exit} + \delta \Delta \mathbf{k}_{ct} + \gamma_{st} + \varepsilon_{bt} \tag{5}$$

Equation (6) is used to estimate the effect of entries/exits that change the distance, d, to the closest hospital using the Medicare data.

$$\Delta y_{bt} = \beta_0^{entry} N_{dt}^{entry} + \beta_1^{entry} N_{dt-1}^{entry} + \beta_0^{exit} N_{dt}^{exit} + \beta_1^{exit} N_{dt-1}^{exit} + \delta \Delta \mathbf{k}_{ct} + \gamma_{st} + \varepsilon_{bt} \tag{6}$$

Like for the AHA data, I report the sum of the entry and exit coefficients, i.e., $\beta^{entry} = \beta_0^{entry} + \beta_1^{entry}$ and $\beta^{exit} = \beta_0^{exit} + \beta_1^{exit}$. For specifications using the Compressed Mortality File, this model is estimating whether a hospital entering or exiting in a demographic group's county of residence, equation (4), or health service area of residence, equation (5), affects the demographic group's mortality rate relative to other areas in the state in that year that are not experiencing entry/exit, controlling for changes in economic activity in the county of residence. The variation used to estimate the parameters of interest in the Medicare data is similar except the bins are finer, so demographic groups are more homogeneous than in the Compressed Mortality File, and the entries/exits are limited to ones that affect the distance the closest hospital. The online appendix includes results for entries/exits in the Medicare data in larger geographic areas.

4.1.3 Estimating the Lives Saved per Unit of Health Care

The point estimate of the lives saved per unit of care is the ratio of the effect of hospital entry or exit on the mortality rate in an area to the effect on a quantity outcome like hospital costs.

For example, the lives saved per unit of health care at an exiting hospital is the effect of exit on mortality divided by the effect of exit on a quantity outcome times a conversion factor that puts the ratio in convenient units (which I describe in section 6). The calculation for entry is identical.

$$\text{Lives saved per unit of care of an exiting hospital} = -\left(\frac{\hat{\beta}^{exit}_{mortality}}{\hat{\beta}^{exit}_{quantity}}\right)(\text{unit conversion factor}) \quad (7)$$

I focus on the number of lives saved per million dollars spent operating the hospital and the number of lives saved per admission. I compute the confidence interval by block bootstrapping over health service areas. The parameter in equation (7) directly answers the question how many lives are saved per million dollars spent operating hospitals on the margin of exiting relative to a counterfactual where it closes, assuming that $\hat{\beta}^{mortality}$ and $\hat{\beta}^{quantity}$ are unbiased. Although, lives saved per admission will overestimate the lives saved per unit of care if hospital entry/exit affects outpatient care that saves lives. Additionally, this measure does not capture benefits of the entering or exiting hospital unrelated to mortality rates.

I focus on the total mortality in an area because it will detect changes in health in the area caused by the exit along a number of margins including patients not being admitted to the hospital, substituting to higher or lower quality hospitals, and developing conditions that risk-adjustment procedures would partial out.

4.2 Identification

The key assumption of the difference-in-differences model is that absent the entry/exit, the trends in the outcome in the treated and control markets would be parallel. The likely source of bias is that hospitals will tend to enter when profits in the market are rising and exit when profits in the market are falling. Changes in profits should be positively related to changes in the quantity outcomes and possibly also to deaths, which would bias $\hat{\beta}^{mortality}$ toward zero and $\hat{\beta}^{quantity}$ away from zero.[15] This is because entry will tend to occur when demand for health care is increasing, and the direct effect of entry should be to reduce deaths and increase the quantity of hospital care. Similarly, exit will tend to occur when demand for health care is falling and the direct effect of exit should be to increase deaths and reduce the quantity of care. This endogeneity problem can be thought of as a reverse causality problem in which decreases in utilization and mortality rates in an area cause exits or increases in utilization and mortality rates cause entries. Given the likely direction of these biases, they could also bias the lives saved per unit of health care toward zero.

Analysis of pre-trends should be able to detect this source of bias because as demand for health care increases, we should observe increases in the quantity of care and potentially the mortality

[15] Chakravarty et al. (2006) find hospital entry and exit is related to proxies for health care demand.

rate. Similarly, exits will tend to occur when demand for health care is falling, which will be preceded by reductions in the quantity of health care and decreases in the mortality rate. If there are no pre-trends, it suggests the assumptions of the difference-in-differences model are not violated and that the bias due to the correlation between demand and hospital entry/exit is small to nonexistent. I show that at the health service area level, there is little evidence of pre-trends for most measures of the quantity of care per capita and the mortality rate. For one outcome there is a pre-trend, but it is removed by including linear health service area-level trends. For that outcome the effect of exit is identified assuming no pre-trend conditional on linear, unit trends (Bilinski and Hatfield 2019). There is also little evidence of pre-trends in two estimators that are robust to biases associated with two-way fixed effects models. Consequently, I can plausibly estimate the effect of hospital entry and exit on these outcomes using the sharp change in access to hospitals caused by the entry or exit.

Even if there are no pre-trends, it is possible the estimates are biased by shocks to profits that immediately cause an entry/exit and are not removed by state-year fixed effects and other controls. There are institutional reasons to believe that local shocks immediately causing entry/exit are uncommon in this setting. In particular, profit shocks are unlikely to immediately cause entry because new hospitals may need to receive regulatory approval to open and hospitals require a substantial amount of time to build. Even exit may be delayed because some states have regulations that slow hospital exits by requiring advance notice or development of plans to manage the exit.[16] Consequently, this source of bias should be small in magnitude and I will use placebo tests to look for evidence of it.

4.3 Tests for Bias

I look for evidence that the parallel trends assumption is violated by estimating the effect of leads and lags of hospital entry and exit on the outcomes of interest. For both the quantity and the mortality data, I check if entry is preceded by increases in the outcomes and if exit is preceded by decreases in the outcomes. The notation is the same as in the first difference specifications but because it is a levels specification, I include unit fixed effects (either health service area, ρ_a, or bin, λ_b, fixed effects). I check if there are trends in the outcomes using AHA data by estimating equation (8),

$$y_{at} = \sum_{j=-6}^{6} \alpha_j^{entry} \Delta N_{a(t-j)}^{entry} + \sum_{j=-6}^{6} \alpha_j^{exit} \Delta N_{a(t-j)}^{exit} + \delta x_{at} + \rho_a + t\rho_a + \gamma_{st} + \varepsilon_{at} \tag{8}$$

and in the binned data by estimating equation (9) for the Compressed Mortality file and equa-

[16] See, e.g., Huron Consulting's list of steps for closing a hospital (Gideon et al. 2015).

tion (10) for the Medicare data.

$$y_{bt} = \sum_{j=-6}^{6} \alpha_j^{entry} \Delta N_{c(t-j)}^{entry} + \sum_{j=-6}^{6} \alpha_j^{exit} \Delta N_{c(t-j)}^{exit} + \delta \mathbf{k}_{ct} + \lambda_b + \gamma_{st} + \varepsilon_{bt} \tag{9}$$

$$y_{bt} = \sum_{j=-6}^{6} \alpha_j^{entry} \Delta N_{d(t-j)}^{entry} + \sum_{j=-6}^{6} \alpha_j^{exit} \Delta N_{d(t-j)}^{exit} + \delta \mathbf{k}_{ct} + \lambda_b + \gamma_{st} + \varepsilon_{bt} \tag{10}$$

Statistically significant, increasing coefficients on the leads of hospital entry or decreasing coefficients on the leads of hospital exit in equations (8)-(10) would indicate the parallel trends assumption is violated. I focus on results for the full model but also present estimates for versions of equations (8) and (9) in the online appendix that only control for unit (health service area or bin) and state-year fixed effects. In nearly all cases these models show no evidence of pre-trends.

I also construct placebo tests to check for evidence of bias in the year of the entry/exit by estimating the effect of entry/exit on outcomes like births or broken hip admissions that are likely related to unobserved shocks and for which I am unlikely to find an effect absent a demand shock. In addition, I check if the effects of entry, for which bias due to contemporaneous shocks is less likely, are similar to the effects of exit. My estimates pass the placebo tests and I cannot reject that the effect of an entry equals the effect of an exit for the quantity of care outcomes.

5 Main Results

5.1 Quantity Estimates

The quantity estimates have two main purposes. The first is to determine if hospital entry and exit has a meaningful effect on access to health care. If hospital exit did not affect the quantity of care, the case for policies to increase access to care, such as subsidizing rural hospitals, would be weakened. The second is to estimate the cost of any health gains or losses associated with hospital entry and exit, which is the denominator in the lives saved per unit of health care calculation.

I check for evidence of pre-trends in the outcome variables by comparing the quantity of care per capita in health service areas experiencing entry or exit to other health service areas in the same state-year after partialing out constant level differences between the health service areas (i.e., estimating a model like equation (8) but only controlling for health service area and state-year fixed effects). There is no evidence of a pre-trend in admissions, inpatient days, or ER visits although there is some evidence of declines in inflation adjusted total hospital operational costs in the years prior to both entry and exit (online appendix figure 3). Adding the full set of controls in equation (8) removes the trends for the effect of exit on hospital costs, which suggests that the specification

adequately controls for any changes in demand for care that precede exit, although the downward trend for entry persists (figure 1). These results indicate the reductions in admissions individual exiting hospitals experience prior to exit are not present at the hospital service area level because as the exiting hospital declines, (1) patients substitute to other hospitals in the area and (2) analyzing the data in per person units eliminates reductions in admissions driven by changes in population in the area.

Each plot in figure 1 shows a sharp change in the quantity of care provided in the year of the event, which indicates that hospital entry increases the quantity of inpatient care and exit reduces it, although the estimates on the lags of entry are generally not individually statistically significant. Hospital exit also sharply reduces the quantity of care in models with limited controls, which indicates the controls are not important for the exit results, while for entry the estimates without controls are noisier and the pattern of results is unclear (online appendix figure 3). The impact of a hospital exit in the plots tends to decrease over time for admissions and inpatient days but not costs or ER visits and the effects are generally not individually statistically significant in later years.

The first differences model estimated using equation (3) finds that an additional hospital results in marginally significant increases in hospital costs per capita of \$52 and inpatient days of 10.1 days while net exit results in significant decreases in costs per capita of $-$\$30 and inpatient days of -7.5 (table 2). The absolute value of the effects of entry and exit are not statistically distinguishable, but the effects of entry tend to be larger. The entry coefficients are less precisely estimated than the exit coefficients because there are fewer entry events. Entry and exit also affect the extensive margin of inpatient treatment. Entry causes a significant increase in hospital admissions and a large but statistically insignificant increase in ER visits, while exit causes significant decreases in both outcomes (table 2).

Next I focus on three areas where the impact of exit on the availability of care should be especially large: rural areas, places where the distance from the exiting hospital to the next closest hospital is in the top two terciles of the distance distribution, and places where the HHI calculated using admissions (as if the hospitals are independently owned) is in the top two terciles of the concentration distribution.[17] The effect of hospital entry and exit in rural areas on utilization is significant or marginally significant for all but one outcome (table 3 and online appendix table 2). It is substantially larger per person than in the full sample, which suggests entry and exit could have a bigger impact on people in rural areas. I also find significant effects of exit in both the distance and concentration specifications and the effect of exit in the more concentrated areas is particularly large (table 3).

[17]The terciles for distance are at about 2 and 10 miles. The terciles for concentration are at 1,300 and 2,725 (concentration increases as the number of hospitals in the area decreases). The HHIs are calculated in health service areas and are not intended to measure concentration in antitrust markets.

The results are robust to using alternative data sources for the outcomes and independent variables of interest. Estimates using the full sample show the effect of hospital exit on hospital operating costs, inpatient days, admissions, and hospital revenue using Medicare Cost Reports from 1999-2010 are also statistically significant, although they are smaller than the estimates using the AHA data (online appendix table 3). Some, but not all, of the estimates for entry are statistically significant. The results are also robust to using a sample of exits collected by Garthwaite et al. (2018), with the exception of the effect on ER visits, which is no longer statistically significant (online appendix table 4). Controlling for hospital mergers using a panel of mergers for the 2000-2010 period from Cooper et al. (2019) reduces the magnitude of entry estimates that were already statistically insignificant and slightly increases the magnitude of the exit results, which remain statistically significant or marginally significant (online appendix table 5). On the whole, the magnitude of the effects on admissions and inpatient days are consistent with the literature, including Raval et al. (2020) who noted admissions fell following a small number of hospital closures caused by natural disasters.[18]

In addition to estimating pre-trends, I check for possible sources of bias using two approaches. First, I find, using an event study version of equation (2), that there is also no evidence the results are biased away from zero by entry/exit causing people to travel between health service areas to receive care because entry/exit does not affect the quantity of health care in neighboring health service areas (online appendix figure 4). Second, births are a plausible placebo test because they are unlikely to be affected by hospital entry/exit unless people travel between health service areas to receive care or there is a shock that matched the timing of the entry/exit. Figure 2 shows that hospital entry and exit have no effect on the number of births in the health service area.

These results show that hospital exit has a substantial effect on the total amount of hospital care received, including on the extensive margin. They also suggest that policies that keep marginal hospitals open increase access to care and result in more patients receiving treatment.

5.2 Main Health Results

In this section I test if hospital entry and exit affect mortality rates in health service areas, to match the level of the entry/exit in the quantity data, and in counties where an event is more likely to affect an individual's access to the hospital. The mortality data are recorded by county of residence, so entry/exit causing people to seek care in neighboring areas cannot influence the estimates.

[18]My estimates are generally smaller than the Joynt et al. (2015) statistically insignificant decrease of 8.4 admissions per 1,000 Medicare beneficiaries and the Carroll (2019) statistically significant decrease in admissions of 8.3 per 1,000 Medicare beneficiaries (table 5 and online appendix figures 5 and 20), smaller than the Rosenbach and Dayhoff (1995) estimate of a 6 percent decrease in discharges and a 8 percent decrease in inpatient days using 11 rural hospital exits (table 3), and similar to the Chung et al. (2017) increase of 19 admissions per bed after three years from hospital construction subsidies (online appendix table 6).

5.2.1 All-Cause and Health Care Amenable Mortality

Figure 3 plots coefficients from regressions of the total mortality rate in units of deaths per 100,000 people on leads and lags of net hospital entry and net hospital exit within an individual's county of residence (equation 9). There is no evidence of a pre-trend and the plots suggest hospital entry and exit do not affect the total mortality rate in the county in the short-term. The long-term results for entries is similar. However, the plots suggest that exit causes long-term reductions in mortality rates. This result implies that on average hospital exits save lives after several years. Consistent with figure 3 the effect of entry and exit in counties on mortality estimated using equation (4) are near zero and statistically insignificant in the short-term (table 2). Estimates of exit in the health service areas show similar magnitude reductions in mortality, but they are statistically significant, which is consistent with exit saving a small number of lives (table 2). The estimates are precise and thus the confidence interval rejects magnitudes much smaller than, e.g., the reduction in mortality caused by some health insurance expansions.[19]

The results for health care amenable mortality, using the definition from Borgschulte and Vogler (2020), are very similar to total mortality both in the short and long-term (table 2 and figure 3). Consequently, the analysis focuses on total mortality.[20] The long-term reduction in total mortality following an exit is robust to a number of alternative specifications including exits in the broader health service areas (online appendix figure 6). In specifications like equation (9), but with limited controls, i.e., only controlling for bin and year fixed effects, there is little evidence of a pre-trend and the exit causes an immediate, persistent reduction in mortality (online appendix figure 7). Similarly, a robustness check using the Garthwaite et al. (2018) sample of exits also shows a decrease in the mortality rate following exit (online appendix figure 8). However, the effect of exit on mortality is not robust to including a county-level trend (online appendix figure 9).

The effect of a hospital entry or exit on mortality should vary with the accessibility of alternative hospitals because if other hospitals are available, patients still will be able to access care relatively quickly in an emergency, their loss of access to care generally is smaller, and any care that patients choose to forgo is likely to be lower value as the increase in travel costs is smaller. Since there is some evidence that exiting hospitals are lower quality than other hospitals average, there could be direct benefits from patients switching to better quality hospitals if one is nearby. To test how the effect of exit varies with the availability of alternative hospitals, I split the sample of

[19] Sommers et al. (2014) found that the Massachusetts health care expansion caused the mortality rate to fall by about 8.2 deaths per 100,000 and Sommers et al. (2012) found that increasing Medicaid enrollment reduced mortality by 19.6 per 100,000.

[20] Amenable deaths are about 75% of total deaths in this sample. If amenable mortality perfectly isolated all the deaths that could be affected by hospital entry and exit, the estimates for total mortality and amenable mortality likely would be approximately equal. The effect of entry/exit on amenable mortality is likely to be somewhat lower than total mortality in absolute value because the definition of amenable mortality excludes some causes of death that may be impacted by access to hospitals and physicians may make errors in identifying the cause of death.

entries and exits by terciles of the distance to the next closest hospital and separately by terciles of concentration measured with HHI in the health service area. These models are identical to equation (9) except there are three sets of leads and lags of hospital entry and exit, one for each tercile.

The plots show the entire long-term decline in mortality in counties following an exit is driven by exits where the effect on access is relatively small, i.e., the next closest hospital is nearby or the concentration is relatively low (figure 4). There is a short-term increase in mortality following hospital exits in the middle tercile of both specifications, which indicates those exits may harm patients, but it is only statistically significant for distance. Estimates for the third tercile are much less precise and there is no clear effect. I also estimate difference-in-differences versions of this specification focusing on net exit and its first lag for events in the top two terciles of the distance and concentration distributions (table 3). The effect of exit on mortality is positive but statistically insignificant for distance. However, the effect of exit on mortality is positive and statistically significant for total mortality in both counties and health service areas, and amenable mortality in health service areas. Consistent with the finding that access is important, mortality increases in rural areas following hospital exit, but the estimates are not statistically significant (table 3 and online appendix figure 10).

These results indicate that the mortality effects of losing a hospital are dependent on the availability of alternatives. If there are sufficient alternatives, there may actually be mortality benefits from the hospital's exit. However, if the next closest hospital is further away or the area is concentrated, there is no evidence of a mortality benefit and some evidence of increased mortality. This suggests that policies designed to prevent hospital exit should focus on hospitals with more limited alternatives.

5.2.2 AMI Mortality and Other Causes of Death

I also estimate the effect of entry/exit on mortality for causes of death for which access to hospital care is likely to be very important to see if the health of this subset of the population is affected by hospital entry/exit. I focus on the AMI mortality rate in an area because it is a cause of death that should be relatively sensitive to access to hospital care. The plot of the coefficients on leads and lags of hospital entry/exit estimated using equation (9) shows little visual evidence of an effect on AMI mortality in the exiting hospital's county (figure 3). However, after adding up the short term effects on AMI mortality using equation (4), exit causes a small but statistically significant increase in AMI mortality of 0.18 deaths per 100,000 in the county the hospital exited (table 2).

These results are not robust to estimating the model using exits in health service areas or using the Garthwaite et al. (2018) sample of exits (table 2, online appendix figure 8, and online appendix table 4). However, models that only control for bin and year fixed effects show a larger increase in mortality, about 2 deaths per 100,000 after 6 years, and there are significant increases in a per bed

specification (online appendix figure 7 and online appendix table 6). There is no clear effect on AMI mortality by distance to the next closest hospital or by concentration (online appendix figure 11).

Additionally, I report event study plots for the effect of entry and exit on 36 causes of death (online appendix figures 12-15). Online appendix figure 12 contains the top 25 causes of death (not in order). The causes with the clearest declines following exit are Alzheimer's disease and ischemic heart disease (chronic and acute diseases related to narrowing of the arteries). Among the less common causes of death, there is a decline for homicides. For context, 74% of gunshot assault victims who visit ERs survive (Kaufman et al. 2020). There is a clear increase in deaths from kidney disease following exits which suggests an additional set of patients that may be harmed. Understanding why hospital exit has differential effects by cause of death is an area for future research that is discussed in more detail in the conclusion.

The suggestive evidence of an effect of hospital exit on AMI mortality in the county is consistent with findings of increased AMI mortality after emergency department closures in the US (Shen and Hsia 2016), after hospital closures in LA County (Buchmueller et al. 2006), and after hospital closures in Sweden (Avdic 2016), but it is not robust to some alternative specifications. More broadly these results indicate some patients may be harmed by typical hospital exits.

5.3 Additional Robustness Checks

I focus on testing the robustness of the main results to alternative definitions of the entry and exit variables, and also check if the results are robust to alternative difference-in-differences estimators. First, I allow the effect of entry and exit to vary freely with all combinations of entries and exits in the data (e.g., one entry and one exit in the same year, one entry and zero exits in the same year, etc.). I interact indicator variables for all combinations of entries and exits with the net entry and net exit variables and their first lags. I re-estimate the main specification replacing the net entry and exit variables with this vector of net entry and exit interactions and an indicator for places with equal numbers of entries and exits.

The first row of online appendix table 7 shows simultaneous entry and exit of one hospital does not have a statistically significant effect on five of the six outcomes. There is a large and statistically significant effect of a single entry (with no exits) on all the quantity outcomes, which is consistent with main results. In places with one entry and two exits, the effect per net exiting hospital is quite large, which suggests entry may have a smaller effect in places with multiple exits than in places with net entry. There are fairly similar sized and generally statistically significant effects of each additional exit on the quantity of care until there are four simultaneous exits. The effect of four exits is small per exiting hospital, which could reflect nonlinearities in the effect of

exit on the outcomes or a very small sample size. The effect of the individual exit variables on total mortality is imprecisely estimated, but there is a marginally significant increase in AMI mortality in places with exactly one exit and the coefficient on AMI mortality is generally positive. These results are consistent with the main specification (section 4.1).

I also check if the net entry and net exit results are robust to using a model that replaces the net entry and exit variables with the number of entries and exits. This approach allows for asymmetry in the effects of all entries and exits, but assumes symmetry in the effects of entry and exit across places with net entry, net exit, and equal numbers of entries and exits. The coefficients and standard errors for exits are almost identical to the main results, but the effect of entry is smaller and not statistically significant (online appendix table 8). The smaller effects of entry are likely explained by the small effect of entry in places with simultaneously exiting hospitals (online appendix table 7).

Finally, I check if the results are robust to alternative difference-in-differences estimators. I limit the sample places with one entry, one exit, or no events, and use a standard two-way fixed effects model. While there are only six entries in this sample, there are 109 exits, which provides a reasonably large sample size to study the effect on utilization. The effect of entry and exit on utilization are of expected sign and statistically significant, but the effects on mortality are imprecisely estimated (online appendix table 9).

Next I use the Sun and Abraham (2021), "SA," event study estimator and Borusyak, Jaravel, and Spiess (2022), "BJS", estimator to estimate the effect of entry and exit with this sample. Event study plots of health care utilization estimated using the SA estimator display no pre-trends and there are sharp, statistically significant decreases following exit. The results for entry are imprecisely estimated (online appendix figure 16). The BJS results are similar, although they are less precisely estimated and only the effects of exit on admissions and ER visits are clearly statistically significant (online appendix figure 17). The SA and BJS estimates for the effect of exit on mortality rates in counties and health service areas are fairly imprecisely estimated, but there are no clear pre-trends (online appendix figures 18 and 19). There are long-term decreases in mortality in health service areas, but it is only statistically significant for the BJS estimator. BJS also shows a marginally significant increase in AMI mortality after exit (for both geographic areas), but there is no evidence of an effect using SA. Overall, the effect of exit on utilization is robust to using these estimators. The robustness of the entry and mortality results is less clear, although there are some mortality results consistent with the main specifications.

6 Lives Saved Per Unit of Health Care: Combining the Quantity and Mortality Estimates

Estimates of the number of lives saved per unit of health care are reported in table 4 for the full sample of events, entries and exits in rural areas, entries and exits in the second and third terciles of the distance to neighboring hospital distribution, and entries and exits in the second and third terciles of the concentration distribution. The later three categories are focused on samples where the effect of exit on access is larger.

To keep the geographic area in which entry and exit happen consistent across the quantity and mortality estimates, I use estimates for health service areas. As an example, the estimate for entry in the full sample is computed using the effect entry on mortality per 100,000 in health service areas divided the effect of entry on costs per capita (table 2). To convert the units to lives saved per million dollars spent, I divide by 100,000 so deaths are per capita, multiply by $\$1,000,000$, and multiply by -1 so ratio is the number of lives saved (rather than deaths averted) per million dollars in hospital costs (values may not match exactly due to rounding):

$$0.0104 = -\left(\frac{-0.54[\text{deaths per 100,000 people}]}{52[\$ \text{ per capita}]}\right)\left(\frac{\$1,000,000}{100,000}\right) \tag{11}$$

The calculation of lives saved per admission uses the effect of entry on admissions per 1,000:

$$0.002 = -\left(\frac{-0.54[\text{deaths per 100,000 people}]}{2.2[\text{admissions per 1,000}]}\right)\left(\frac{1,000}{100,000}\right) \tag{12}$$

The calculation for exits is symmetric. The calculation for rural areas and the top two terciles of the distance and concentration distributions take the same approach using table 3 for exits and online appendix table 2 for entries. I estimate the confidence interval of the ratios by block bootstrapping over health service areas.

The point estimate for the effect of entry is 0.10 lives saved per million dollars of hospital costs. This estimate is consistent with entries saving lives but it is imprecise and the confidence interval spans 0.63 lives lost to 1.9 lives saved per million dollars spent (table 4). The corresponding estimates for exit suggest the average exit reduces mortality with a point estimate of -0.15 lives saved per million dollars, i.e., that increasing hospital spending by $1,000,000 would cost 0.15 lives. The confidence interval rejects more than 0.05 lives saved per million dollars spent, which is very close to zero. For comparison purposes, a statistical value of a life of $20 million is equivalent to 0.05 lives saved per million dollars spent. The estimated lives saved per admission is also negative with a confidence interval that can reject that less than about 500 patients would need to

be admitted in order to save an additional life.[21] Longer-term estimates that use the total effect of entry and exit six years after the event are similar, e.g., a point estimate of -0.53 lives saved per million dollars spent (online appendix table 10).

In rural areas the point estimate for exit is 0.34 lives saved per million dollars spent, which is equivalent to a cost-per-life saved of about $2.9 million. The confidence interval includes negative lives saved estimates and the upper bound of the confidence interval is about 1.15 lives saved per million dollars spent, which is equivalent to a cost-per-life saved of about $870,000. This suggests the cost of saving a life for rural hospitals on the margin of exiting could be much lower than the average hospital but is quite uncertain. Longer-term estimates that use the total effect of entry and exit in the six years after the event are similar (online appendix table 10).

The point estimate for exits with more distant neighbors is 0.52 lives saved per million dollars spent or a cost-per-life saved of $1.9 million, but it is not statistically significant (table 4). The upper bound of the confidence interval includes a cost-per-life saved of $175,000. The estimates for exits in more concentrated areas are similar, but are more precisely estimated. The effect of exit on lives saved per million dollars is a statistically significant 0.45 or a cost-per-life saved of $2.2 million. The estimate for lives saved per admission is also statistically significant. The long-term effects for exits by distance are negative but the long-term effects for exit by concentration larger and are statistically significant for one measure (online appendix table 10).

Lives saved per unit of care is closely related to the cost per life-year saved, which is often approximated as the cost of care divided by the number of lives saved over a single year. Typical threshold values used in cost-effectiveness analysis are in the range of $100,000-$200,000 (Doyle et al. 2015), or about 5 to 10 life-years saved per million dollars in spending, although standard estimates of the value of a statistical life (rather than a life-year) would imply fewer lives saved per million (Aldy and Viscusi 2008). My full sample, rural, and concentration results can reject effects of that magnitude.

My estimates suggest the cost of saving a life is high relative to related estimates in the literature in the literature. For example, Doyle et al. (2015) finds a cost per life-year saved of about $80,000 for high intensity care for individuals arriving to the hospital by ambulance, and notes that cardiac catheterization produces values in the same ballpark (Chandra and Staiger 2007, McClellan and Newhouse 1997). Almond et al. (2010, 2011) estimates a cost per life-year saved of high intensity treatment on low-birth-weight babies of $527,000-$1.3 million,[22] and Doyle (2005)

[21]The lives saved per million dollars is overestimated if non-hospital outpatient care increases following an exit. However, exit does not cause substitution between hospital and non-hospital care in the Medicare data and the effect on total expenditures is larger than the effect on acute inpatient expenditures (online appendix figures 20 and 23 and table 5).

[22]Estimates of the decrease in mortality are much smaller if data close to the cut off are dropped (Barreca et al. 2011, Almond et al. 2011).

estimates a cost per life-year saved from having health insurance after a car accident of $220,000. The estimates across these papers imply 0.77 to 12.5 lives saved per million dollars spent. The estimates of the marginal return on care in most of these papers is outside the exits confidence interval and would be detectable if they existed in my data.

Carroll (2019) estimates that critical access hospital exits reduce Medicare spending by about $9 million annually and result in 70 deaths annually, which is a cost-per-life-saved to Medicare of $129,000. She calculates that exiting hospitals save about $120 million per year in fixed costs or about $1.7 million per life saved, assuming about half of total costs are fixed. This estimate is similar to my estimates for exits in rural areas, exits with more distant neighbors, and exits in more concentrated places, although the $120 million was not directly estimated and the calculation assumes the only lives lost are Medicare patients admitted for time-sensitive conditions.

An important consideration when interpreting these results is that mortality rates do not capture the full benefit of hospitals. Hospital exit could harm patient health without reducing the mortality rate by a detectable amount. Additionally, patients value access to hospitals close to home (Raval and Rosenbaum 2021). A consequence of a hospital exit is reduced competition like following mergers which can lead to reductions in patient satisfaction (Beaulieu et al. 2020), hospital price increases that are passed on to workers in the form of lower wages (Cooper et al. 2019 and Arnold and Whaley 2021), and lower wage growth for nurses and pharmacy workers (Prager and Schmitt 2021). A loss of a hospital could have broader effects on the community too. Hospital psychiatric unit closures increase ER utilization and crime (Sachs 2019). Although not all effects of hospitals are necessarily beneficial. Rural maternity ward closures led to reduced caesarean section rates for low risk patients with no evidence of effects on access to care or maternal and infant health (Battaglia 2022 and Fisher et al. 2022).

7 Marginal Patients

In this section I focus on understanding two mortality results that contribute to finding a low number of lives saved per million dollars spent. First, why do the reductions in inpatient health care following hospital exit not increase mortality on average? Second, why does the effect on mortality vary with access to alternative hospitals? To explore these questions I use detailed Medicare data with measures of the distance to the hospital, the severity patients' diagnoses, and hospital quality. I focus on hospital entries/exits most likely to affect patients, entries and exits of patients' closest hospital. These are entries that reduce patients' distance to the hospital and exits that increase patients' distance to the hospital.

7.1 What explains the short-term null effect of exit on mortality?

I start by replicating the main results using the Medicare data focusing on the entry or exit of Medicare beneficiaries' closest hospital using equation (6). As expected, the effect of entry on the quantity of care is positive, the effect of exit is negative, and both effects are large and less precisely estimated relative to the estimates using AHA data (table 5). Only the effects on admissions and ER visits are statistically significant. Event studies estimated using equation (10) show fairly convincing evidence of effects on both admissions and ER visits (online appendix figure 20). This suggests the quantity effects estimated with AHA data are not due people traveling between health service areas to receive care. Similar to the analysis using the Compressed Mortality File, there are no short-term significant effects on total mortality for people living near the hospital, but the estimates are imprecise. The effects on AMI mortality are also statistically insignificant, but there is statistically significant evidence that entry reduces or exit increases certain broader categorizations of heart related causes of death (online appendix figures 21-22).

The effect of exit on inpatient care and the mortality rate in counties could be attenuated if the exiting hospital is converted to a nursing home. I find exit does not affect utilization at skilled nursing facilities, a type of nursing home that provides higher acuity services. This lack of substitution between hospitals and skilled nursing facilities suggests these facilities are not substitutes and thus conversion of exiting hospitals to nursing homes is unlikely to affect the results (online appendix figure 23).

Next I check whether patients induced to forgo inpatient hospital care by an exit have less severe medical conditions than average. If the marginal patients are not among the sickest patients, there could be reductions in admissions without increases in mortality. I construct weighted average measures of the severity of admitted patients' conditions using their diagnoses. First, I compute the average in-hospital death rate across all patients by primary diagnosis and assign each admitted patient the average death rate associated with their primary diagnosis. If a patient is admitted with a diagnosis that has an average in-hospital mortality rate of 0.05 across the entire sample of patients, their value of the index will be 0.05, regardless of the mortality rate at their hospital. This index will be higher when a patient is admitted for a diagnosis that is more severe. The second measure is the Charlson Index, for which higher values also mean the admitted patient has more severe diagnoses.

Figure 5 shows the effect of hospital entry and exit on these indices estimated using equation (10). There is no evidence of an effect of entry on the Charlson Index and the effect of entry on the death rate index is uncertain because there appears to be a pre-trend. However, there are clear increases in both indices following exit of the nearest hospital. This result indicates that after an exit, the average admitted patient has more severe conditions than prior to the exit. This finding suggests the effect of exit on admissions is driven by patients with less severe than average

conditions, which should tend to mitigate the potential harm to patients caused by exits because relatively healthy patients are disproportionately forgoing inpatient care.

Next I test how entry and exit affect the average quality of the hospitals patients are admitted to measured using risk-adjusted in-hospital AMI and heart failure mortality, two AHRQ quality indicators. I construct these quality indicators assuming hospital quality is constant across the sample period after removing year fixed effects (i.e., trends in measured quality). Higher values of the index imply beneficiaries are being admitted to hospitals with higher risk-adjusted mortality rates, i.e., where they are more likely to die conditional on observable characteristics. A concern with measuring hospital quality in this way is that unobservably sicker patients tend to select relatively higher quality hospitals, which compresses the distribution of measured hospital quality (Hull 2020). This sorting will bias the effect of exit on measured quality toward zero, and thus I am likely underestimating the effect of exit on utilized hospital quality.

I estimate the effect of hospital entry and exit on the average risk-adjusted mortality rate of the hospitals Medicare beneficiaries are admitted using equation (10). Figure 6 shows that following an entry that reduces the distance to the closest hospital, the average heart failure index falls, which is consistent with entry causing patients to be admitted to higher quality hospitals (with lower risk-adjusted in-hospital mortality rates), but there is no effect on the average risk-adjusted in-hospital AMI mortality index. Following an exit of the closest hospital, there is no effect on the average heart failure index, but there is a significant decrease in the risk-adjusted in-hospital AMI mortality index. This pattern of results indicates exit causes patients to be admitted to hospitals that are better at treating AMI. The effects on quality are relatively small, somewhat less than 1/10 of a standard deviation. These improvements in average hospital quality will tend to offset some of the harm potentially caused by the reduced care at hospitals following an exit.

Together, these results suggest that people who forgo hospital care because of an exit have less severe than average conditions, and that the ones who are admitted despite the exit go to better quality hospitals on average. Both forces tend to reduce the effect of hospital exit on mortality. The former force tends to limit the potential harm caused by exit while the later effect could actually lead to reduced mortality rates for some patients.

7.2 Why do effects on mortality vary with distance to the hospital?

For the effect of hospital exit on mortality to vary with the distance to the hospital, there would need to be factors that affect whether exit harms patients that also vary with the distance to the hospital. In particular, for exiting hospitals with nearby substitutes to benefit patients in the long run while exits with more distant substitutes to harm patients, it is plausible the effect of exit on admissions and diagnosis severity would vary with the distance to the hospital. To test this hypoth-

esis I estimate effects of entry and exit by the change in distance to the hospital on admissions and by patient diagnoses.

To see how the effect of exit varies with the distance to the hospital, I divide the entries and exits into terciles by the change in distance to the nearest hospital. This model is identical to equation (10), except there are three sets of leads and lags of hospital entry and exit, one for each tercile of distance to the hospital. I find that entries only significantly affect inpatient admissions for patients with the largest decrease in distance to the nearest hospital (over 4.6 miles). For exits there is some evidence of a reduction in admissions in all three terciles, but the effect is monotonically increasing as the distance to the next closest hospital gets larger (figure 7). More broadly, hospital entry and exit have larger effects on admissions the closer the Medicare beneficiary is to the entering/exiting hospital (online appendix figure 5). These results suggest that the loss of a nearby hospital on inpatient care is mitigated to some extent by access to another nearby hospital. Patients who do not have to travel much further to the hospital experience smaller reductions in care after an exit, which suggests they are less likely to be harmed than patients who must travel much further to the hospital.

I also examine the effect of exit on inpatient admissions for the top 40 diagnoses, ordered by the share of admissions that happen on weekends, which is a measure of patients' willingness to defer treatment (Card et al. 2009).[23] I again divide the entries/exits into terciles by the change in distance to the nearest hospital and estimate equation (6) for entries/exits in each tercile. The plotted coefficients are the sum of the effect of an exit in the year of the event and the subsequent year. I focus on exits in the first tercile where the change in distance to the hospital is the smallest and the third tericle where the change in distance to the hospital is the largest.

In the first tercile, where increase in distance to the hospital is the smallest, there are significant reductions in admissions for dehydration, bilary tract disease (e.g., diseases of the bile ducts or gallbladder), and rehabilitation (which does not include substance abuse rehab) and there is an increase in admissions for respiratory failure (figure 8). In the third tercile, where the increase in distance to the hospital is the greatest, there continue to be reductions in admissions for dehydration and there are also significant reductions in admissions for intestinal obstruction, urinary tract infections (UTI), pneumonia, and skin infection. Thee effects on less deferrable conditions in the third tercile suggest relatively large changes in access to hospitals reduces care for patients with more severe conditions. However, across both terciles there is never an effect on admissions for diagnoses for which I would expect demand to be extremely inelastic, e.g., broken hips (figure 8).

The pattern of effects by diagnosis suggests the potential harm from exits of hospitals with nearby alternatives will be limited by the fact that the marginal patients do not have the most severe diagnoses, but there is some evidence exit could lead to harm for larger changes in access to the

[23] Admissions are measured using claims. Less than 2 percent of claims are from an ongoing hospital stay.

hospital because some of the marginal patients have more severe conditions. These results indicate exit could even lead to lower total mortality when another hospital is nearby, because exit causes patients to substitute toward higher quality hospitals on average, relatively fewer people forgo care when another hospital is nearby, and the people who forgo care have relatively deferrable conditions.[24]

8 Conclusion

I show hospital entry and exit affect the amount of hospital care along the extensive margin in both the aggregate data and for Medicare beneficiaries. I find little evidence of an effect on diagnoses for which demand for inpatient care should be very inelastic (e.g., births and broken hip admissions). The quantity effects are driven by entries/exits that result in relatively large changes in distance to the nearest hospital and among patients that do not have the most severe diagnoses.

On average entries and exits do not lead to short-term changes in the mortality rate in the area around the hospital, but there is some evidence that reduced access to hospitals increases AMI and kidney disease mortality in the county by a small amount. In the longer term there is evidence that some exits actually benefit patients by reducing the overall mortality rate when there are readily available alternatives. The results suggest the cost of saving a life by preventing exit is high on average with a confidence interval that rejects estimates of the marginal return on health care found in a number of papers in the literature and standard estimates of the statistical value of a life-year. Thus, preventing the average hospital from exiting that is on the margin of shutting down is not a cost effective way to save lives. However, this result is driven by hospitals with readily available alternatives. There is some evidence that exits cause mortality to increase when the next closest hospital is not very close by or when the there are fewer alternatives as measured by concentration. The cost of saving a life at hospitals whose exit has a larger impact on access to care is far lower although still substantial.

An important limitation of the results is that mortality rates do not capture the full benefit of hospitals. Increased access to hospitals could lead to better health or have other positive effects without reducing the mortality rate by a detectable amount. For example, figure 8 shows reduced admissions for skin infections, which are unlikely to affect mortality but may provide some difficult to quantify benefits to patients (Mower et al. 2019). Access to hospitals and hospital competition have other benefits to patients and their communities beyond their effect on mortality rates (e.g., Arnold and Whaley 2021, Beaulieu et al. 2020, Prager and Schmitt 2021; Raval and Rosenbaum

[24] While the quality of the hospital patients are admitted to improves after exit, the effect of exit on quality is slightly increasing as the distance to the next closest hospital increases from the first to third tercile (online appendix figure 24).

2021). These estimates are also most directly applicable to hospitals on the verge of exiting, and do not imply that the marginal return on care at the typical hospital is low or that the benefit of care of the marginal entrant is low. However, this is a relevant estimate for evaluating policies designed to prevent exit. Finally, the results are based on a two-way fixed effects estimator. The effect of exit on the quantity outcomes is robust to using the Sun and Abraham (2021) and Borusyak, Jaravel, and Spiess (2022) estimators, but the entry estimates and estimates of the effect of exit on mortality are imprecise and it is hard to draw firm conclusions about their robustness.

A potential area for future work is studying why hospital exit may have differential effects by cause of death. Results in section 5.2.2 show that on average exit reduces the mortality rate for certain acute and chronic conditions, while showing clear evidence of an increase in mortality for a disease category that includes both acute and chronic illness, kidney disease. The effect of exit on mortality could plausibly vary depending on the time sensitivity of the condition, the travel time to the next closest hospital, the quality of care the exiting and alternative hospitals for the relevant conditions, and additional considerations particular to certain causes of death. For example, there is a recent literature showing that dialysis center market structure and reimbursement policies affect mortality rates (Eliason et al 2020, Eliason et al 2022, and Wollman 2020). Effects of exit may even vary within categories of disease, like kidney disease, which includes both chronic and acute conditions.

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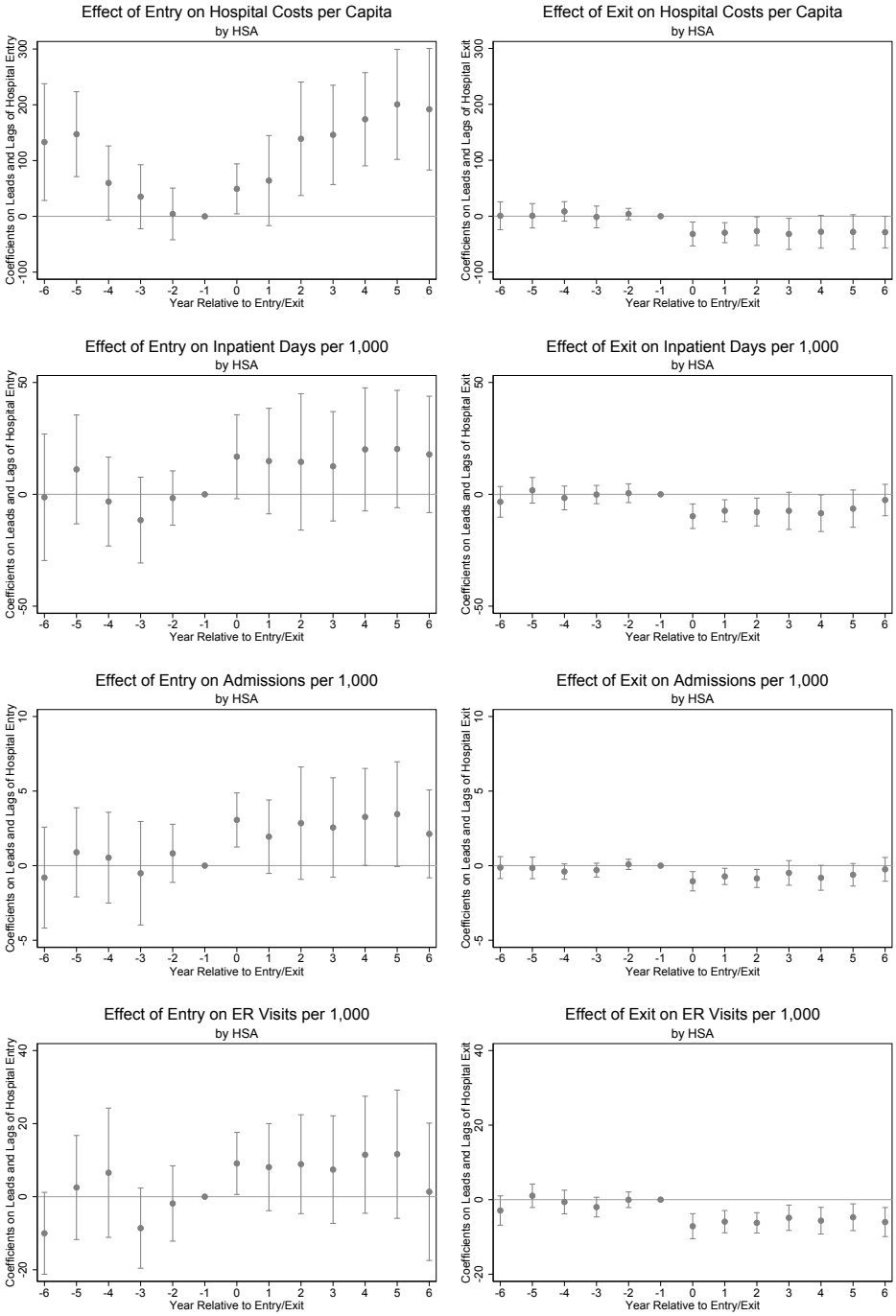
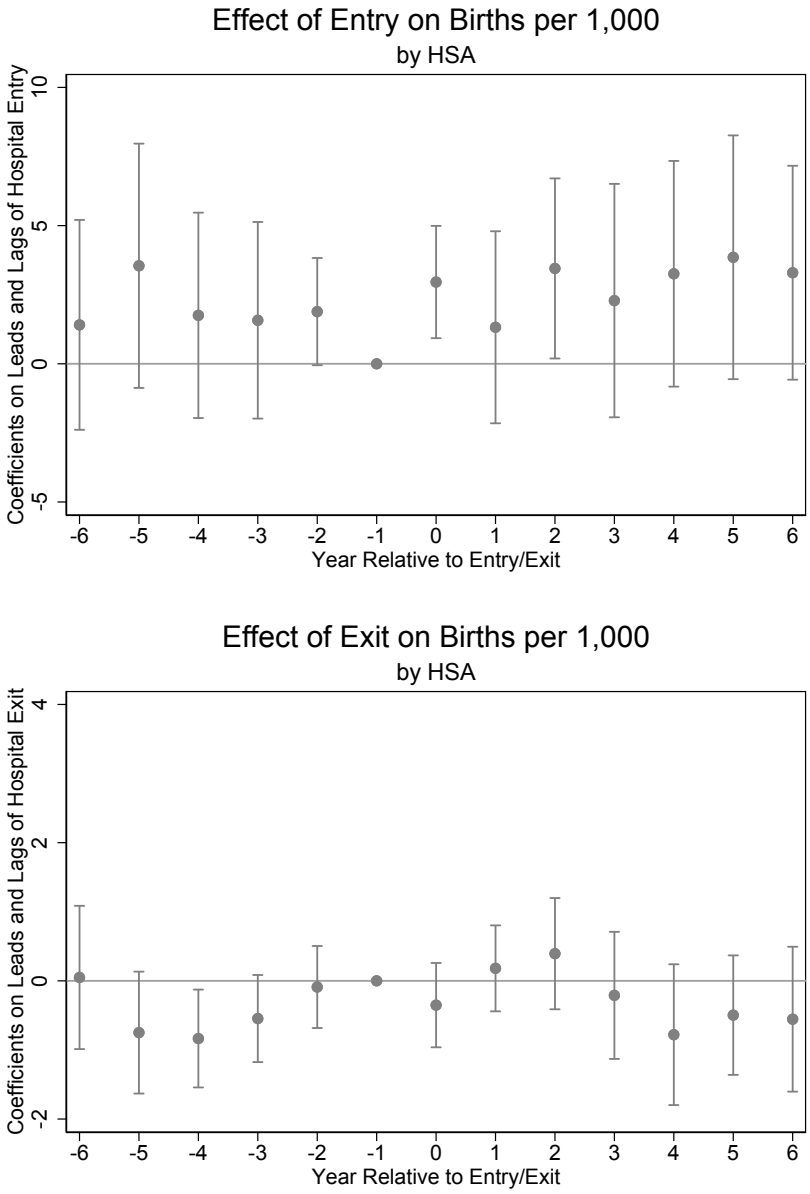
Figure 1: Effect of Hospital Entry and Exit in Health Service Areas on the Quantity of Treatment



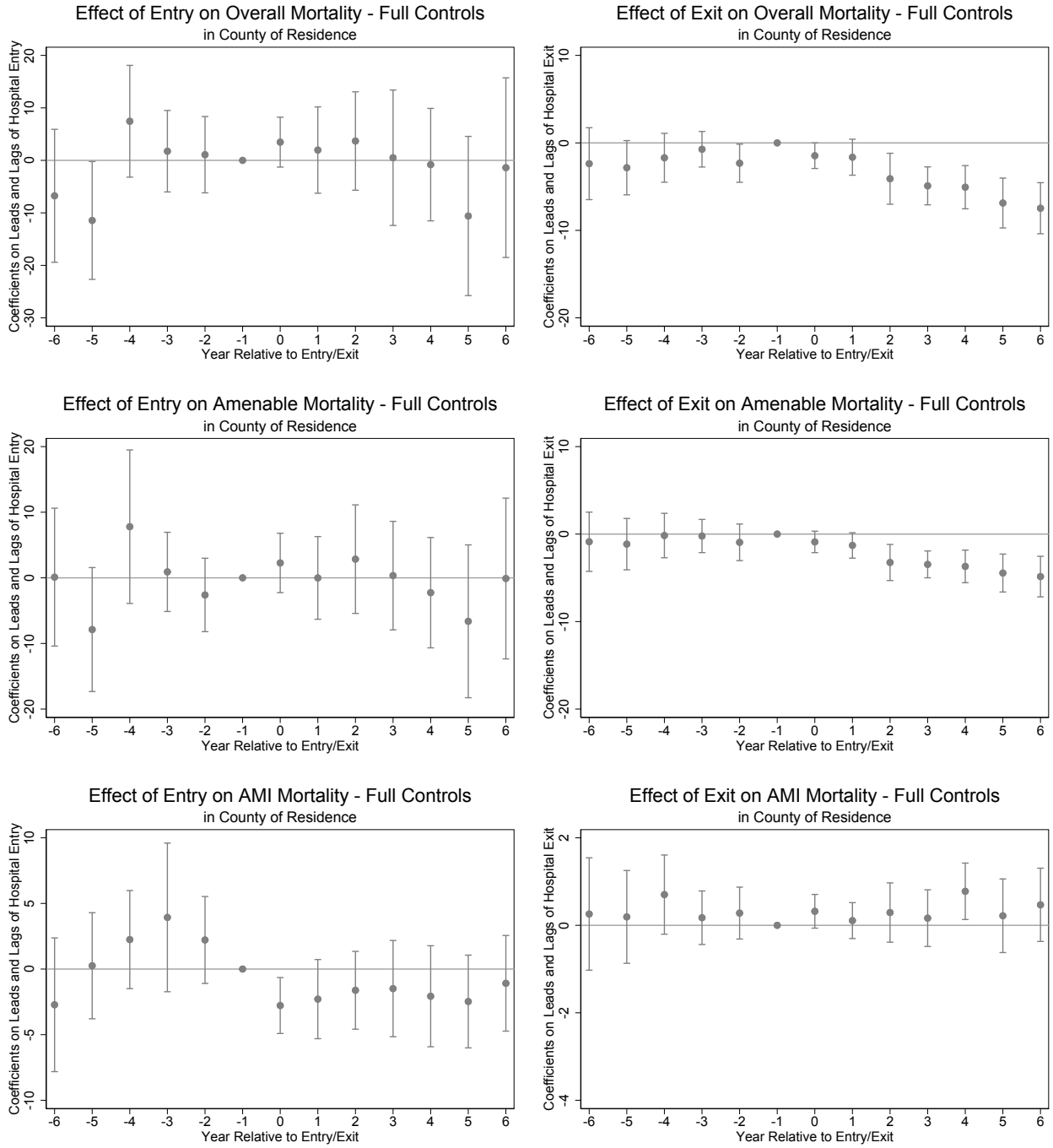
Notes: Data cover the 1982-2010 period. The unit of analysis is the health service area-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry or exit where the coefficient on the one-year lead is normalized to zero. The figures plots estimates from population weighted regressions of the level of the outcome variable on leads and lags of the change in the number of hospitals from entry, the change in the number of hospitals from exit, health service area fixed effects, state-year fixed effects, health service area time trends, and demographic and economic activity controls. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 2: Effect of Hospital Entry and Exit in Health Service Areas on Births



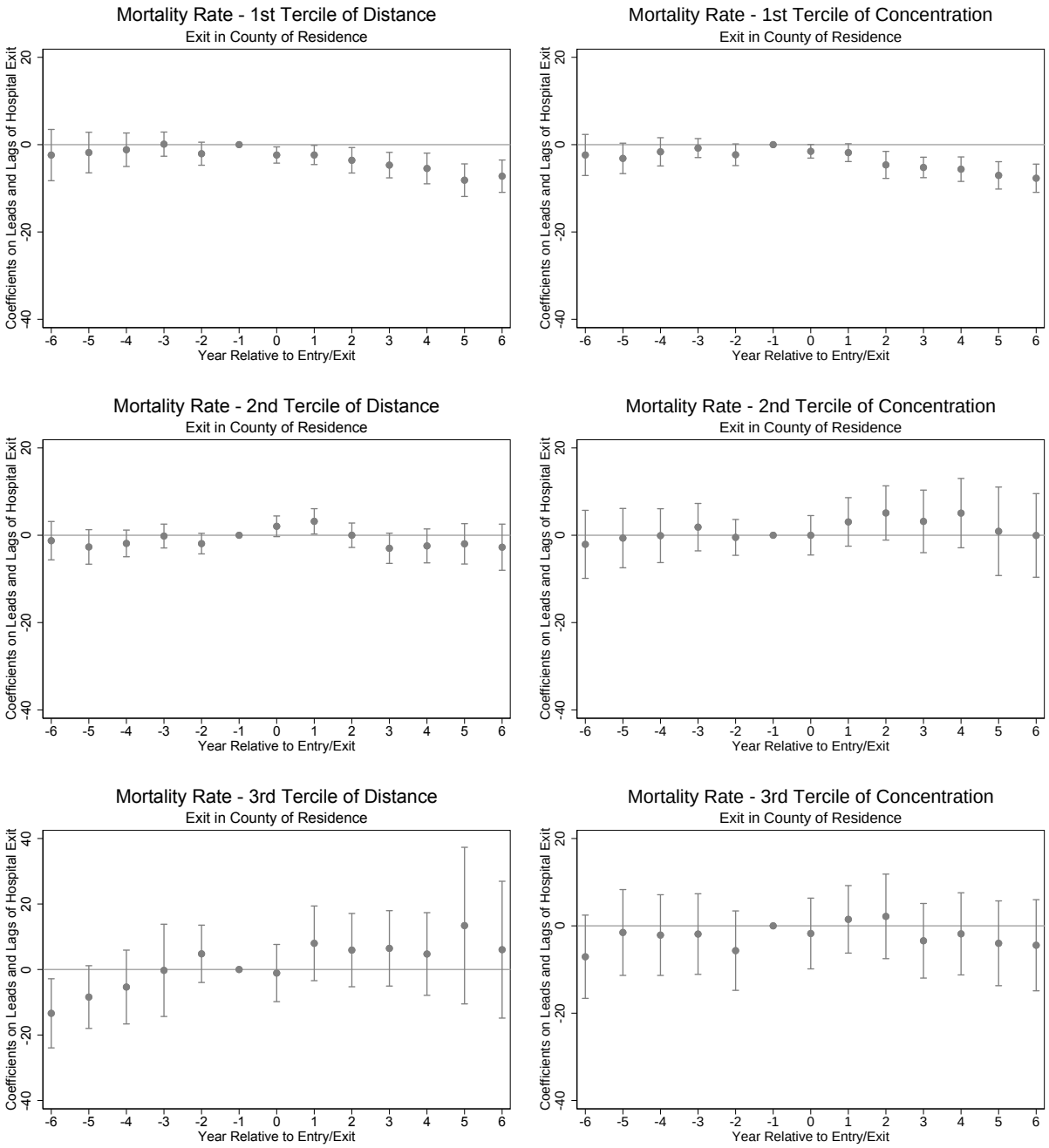
Notes: Data cover the 1982-2010 period. The unit of analysis is health service area-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry and exit where the coefficient on the one-year lead is normalized to zero. Plots are estimates from population weighted regressions of the level of the outcome variable on leads and lags of the change in the number of hospitals from entry and exit, health service area fixed effects, health service area time trends, state-year fixed effects, and demographic and economic activity controls. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 3: Effect of Entry and Exit in Counties on the Mortality Rate



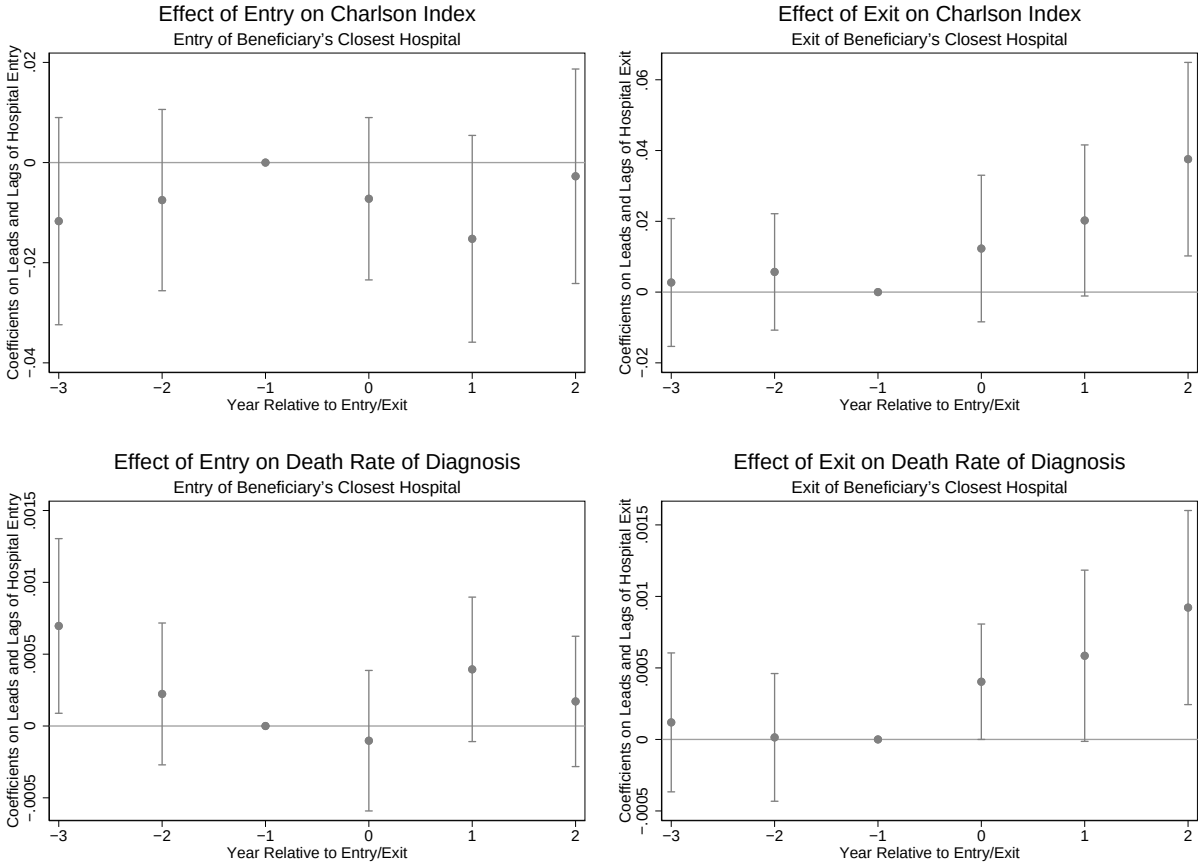
Notes: Data cover the 1982-2010 period. The unit of analysis is the county-race-gender-age group-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry and exit using population weighted regressions of the total mortality rate or AMI mortality rate on leads and lags of the change in the number of hospitals from entry and exit. The plotted coefficients are estimated controlling for county-race-gender-age group fixed effects, state-year fixed effects, and economic activity controls. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 4: Effect of Hospital Exit in Counties on the Mortality Rate by Distance to Next Closest Hospital and Health Service Area Concentration



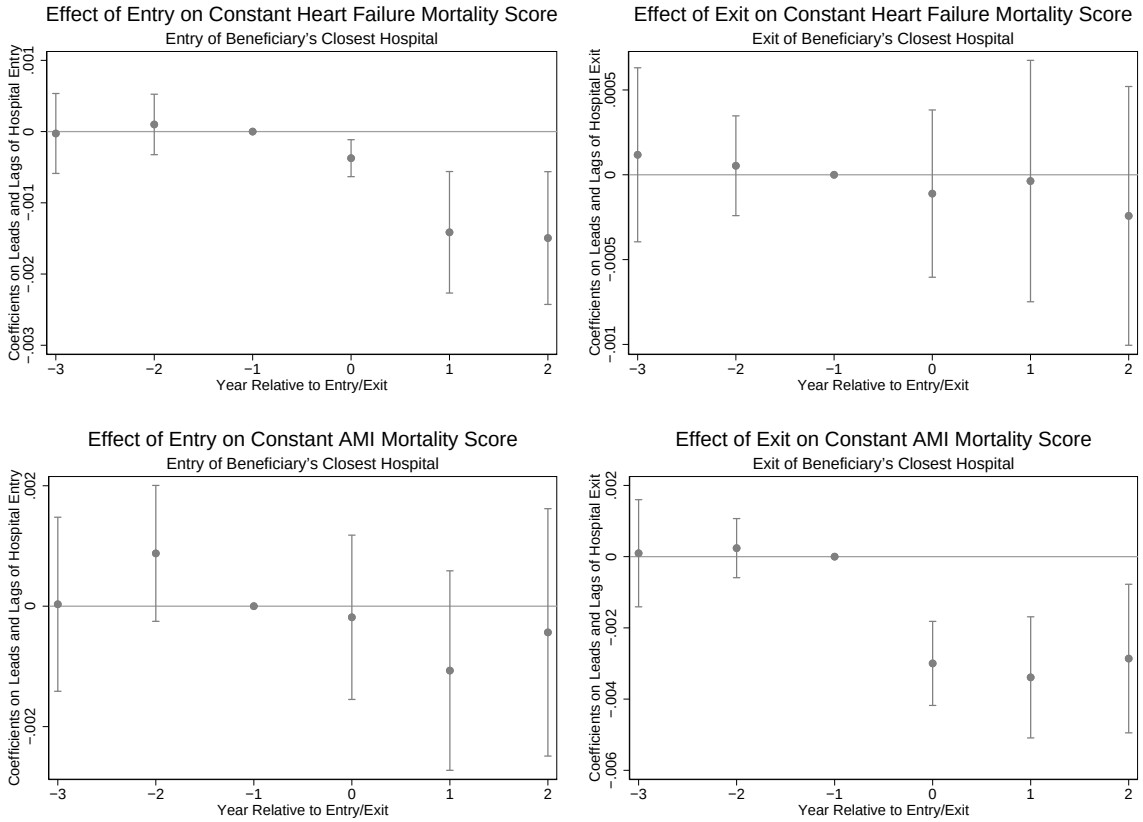
Notes: Data cover the 1982-2010 period. The unit of analysis is the county-race-gender-age group-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from exit using population weighted regressions of the total mortality rate on leads and lags of the change in the number of hospitals from entry or exit by tercile of distance to the next closest hospital or health service area concentration, county-race-gender-age group fixed effects, state-year fixed effects, and controls for economic activity. The entries and exits are split into terciles by distance to the next closest hospital or concentration. The distance to the closest hospital is shortest in the first tercile and farthest in the third tercile. Concentration is HHI calculated using admissions (as if the hospitals are independently owned). The first tercile is the lowest level of concentration and the third is the highest. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 5: Effect of Entry and Exit of the Closest Hospital on Average Diagnosis Severity of Medicare Beneficiaries Admitted to the Hospital



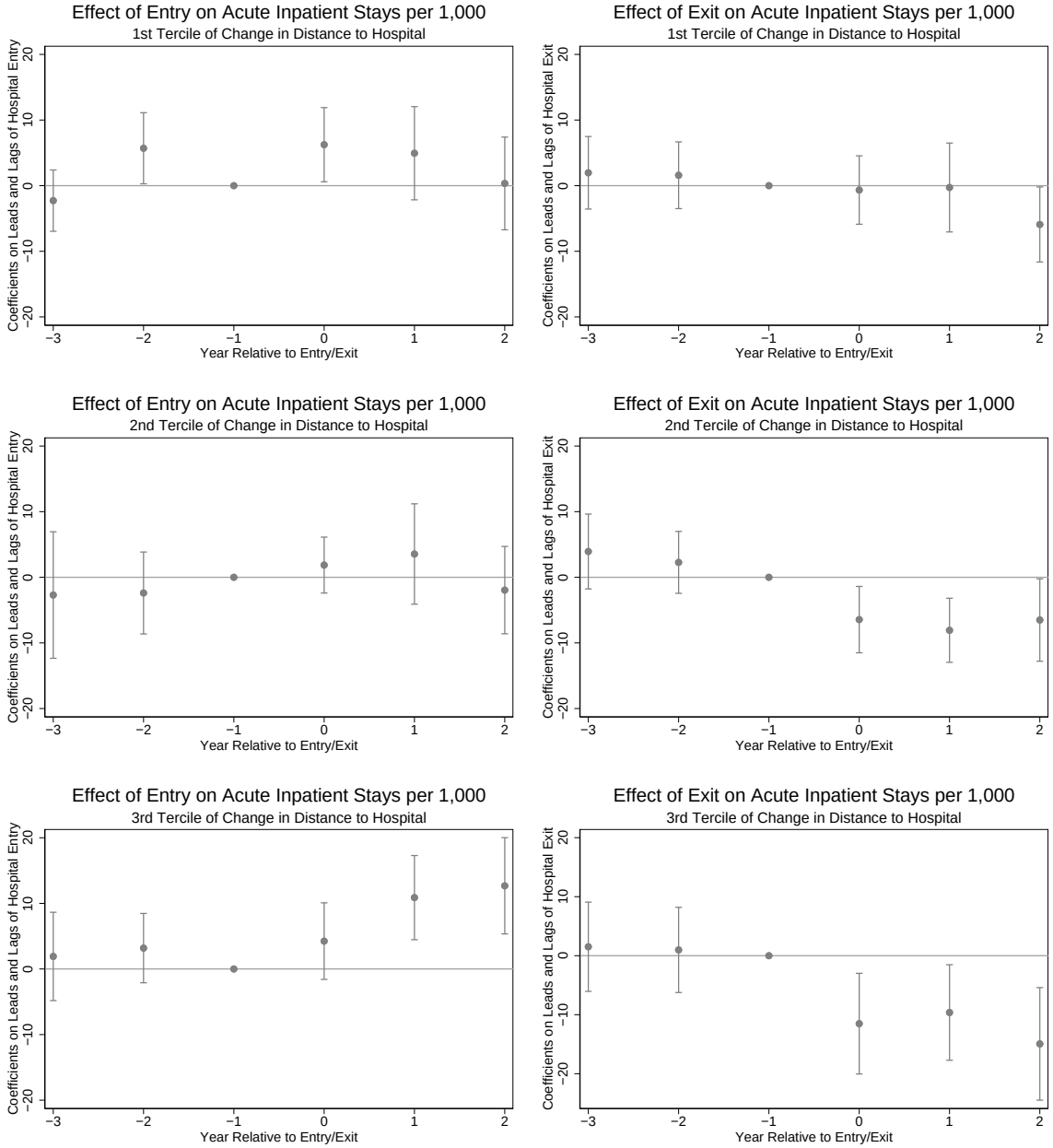
Notes: Data cover the 1999-2011 period. The unit of analysis is the cohort-race-sex-zip code-county-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry and exit that affects the distance to the closest hospital, normalized so the coefficient on the one-year lead is zero. The coefficients are from a regression of the level of the outcome on leads and lags of the change in the number of hospitals from entry and exit and controls including state-year fixed effects, economic activity controls, and cohort-race-sex-zip code-county fixed effects. The regressions are weighted by the number of Medicare beneficiaries in each bin and the outcomes are all in per-beneficiary units. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 6: Effect of Entry and Exit of the Closest Hospital on Average Hospital Quality for Medicare Beneficiaries



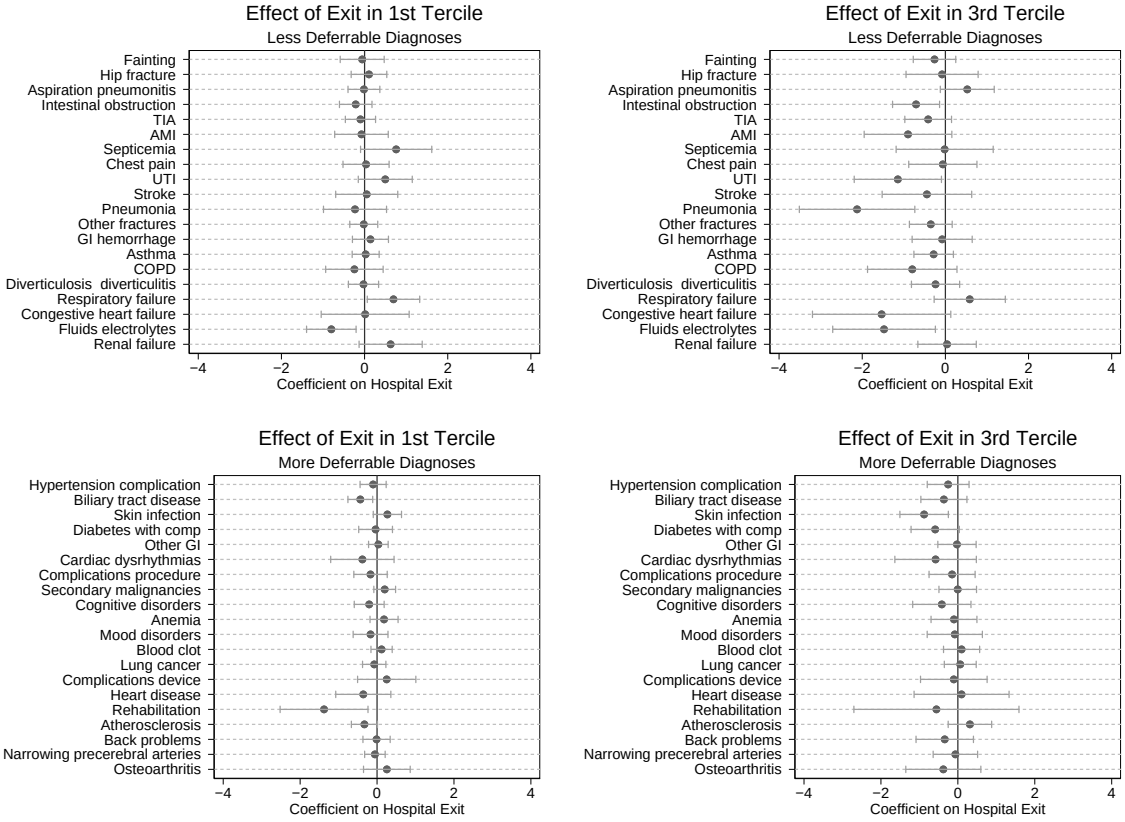
Notes: Data cover the 1999-2011 period. The unit of analysis is the cohort-race-sex-zip code-county-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry and exit that affects the distance to the closest hospital. The coefficients are from a regression of the outcome on leads and lags of the independent variable of interest and controls including state-year fixed effects, economic activity controls, and cohort-race-sex-zip code-county fixed effects. The regressions are weighted by the number of Medicare beneficiaries in each bin. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area.

Figure 7: Effect of Entry and Exit of the Closest Hospital on Admissions of Medicare Beneficiaries by Terciles of the Change in Distance to the Nearest Hospital



Notes: Data cover the 1999-2011 period. The unit of analysis is the cohort-race-sex-zip code-county-year. Plots are of coefficients on leads and lags of the change in the number of hospitals from entry and exit that affects the distance to the closest hospital for terciles of the change distance to the hospital. The coefficients are from a regression of the outcome on leads and lags of entry and exit in the tercile, state-year fixed effects, economic activity controls, and cohort-race-sex-zip code-county fixed effects. The regressions are weighted by the number of Medicare beneficiaries in each bin. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area. Terciles are ordered from smallest (first tercile) to largest (third tercile) change in distance to the closest hospital.

Figure 8: Effect of Exit of the Closest Hospital on Inpatient Admissions of Medicare Beneficiaries by Diagnosis and Terciles of the Change in Distance to the Nearest Hospital



Notes: Data cover the 1999-2011 period. The unit of analysis is the cohort-race-sex-zip code-county-year. Plots show the top 40 diagnoses during the sample period ordered by the share of admissions that occur on weekends. The plotted coefficients are from a regression of changes in the outcome on the change in the number of hospitals from exits that affect the distance to the closest hospital and its first lag by tercile of the change in distance to the next closest hospital. The controls include entry and its first lag in the tercile, economic activity controls, and state-year fixed effects. The regressions are weighted by the number of Medicare beneficiaries in each bin and the outcomes are in per-1,000-beneficiary units. The plotted coefficients are the linear combination of the sum of the on-impact effect plus the one-year lag. Error bars show the 95-percent confidence interval. Standard errors are clustered by health service area. Terciles are ordered from smallest (first tercile) to largest (third tercile) change in distance to the closest hospital. The middle tercile is not reported to simplify the presentation.

Table 1: Characteristics of Entering or Exiting Hospitals Relative to Other Hospitals in the Same Health Service Area

Dependent Variable:	Has ICU Beds	Beds	Inpatient Days Per Bed	Average Length of Stay	Cost per Inpatient Day
Entering Hospital in	-0.05	-128	-120	-1.23	57,629
Year of Entry	(0.05)	(11)	(5)	(0.27)	(42,945)
Exiting Hospital in	-0.31	-103	-47	1.22	2,451
Year Before Exit	(0.02)	(6)	(3)	(0.31)	(1,051)
Constant	0.80	162	193	5.85	5,233
	(0.0001)	(0.05)	(0.02)	(0.002)	(31)
HSA-Year FE	X	X	X	X	X
# HSAs	805	805	805	805	805
# Observations	132,949	150,519	150,512	150,512	150,512

Dependent Variable:	Risk-Adjusted Readmissions			Patient Satisfaction	
	AMI	Heart Failure	Pnemounia	Score	Recommend
Entering Hospital	-0.0013	-0.0007	0.0012	0.068	0.076
	(0.0013)	(0.0026)	(0.0014)	(0.020)	(0.019)
Exiting Hospital	0.0015	0.0032	-0.0002	-0.077	-0.081
	(0.0020)	(0.0042)	(0.0022)	(0.024)	(0.024)
Constant	0.1992	0.2453	0.1817	2.524	2.610
	(0.00002)	(0.00004)	(0.00002)	(0.0003)	(0.0003)
HSA FE	X	X	X	X	X
# HSAs	649	795	802	796	796
# Observations	2,709	4,228	4,417	4,483	4,483

Dependent Variable:	Risk-Adjusted Mortality		
	AMI	Heart Failure	Pnemounia
Entering Hospital	-0.0011	-0.0039	-0.0059
	(0.0020)	(0.0013)	(0.0028)
Exiting Hospital	0.0039	0.0010	0.0044
	(0.0017)	(0.0016)	(0.0020)
Constant	0.1616	0.1114	0.1145
	(0.00003)	(0.00002)	(0.00003)
HSA FE	X	X	X
# HSAs	787	800	803
# Observations	4,044	4,427	4,551

Note: The top panel uses data that cover the 1982-2010 period and the unit of observation is a hospital-year. The bottom two panels use entry/exit data from 2005-2011 and the unit of observation is a hospital. Numbers reported in the entering and exiting hospital rows are coefficients and standard errors (in parenthesis, clustered by health service area) from regressions of the level of each dependent variables on either indicators for the year a hospital enters and the year before a hospital exits and health service area-year fixed effects (top panel) or indicators for hospitals that entered or exited during the 2005-2011 period and health service area-fixed effects (bottom two panels).

Table 2: Effect of Entries and Exits on Quantity and Mortality

Dependent Variable:	Utilization			
	Cost per capita	Inpatient Days per 1,000	Admissions per 1,000	ER Visits per 1,000
	In Health Service Areas			
Number of Hospitals + First Lag:				
Net Entries	52	10.1	2.2	5.1
	(26)	(5.4)	(1.1)	(5.3)
Net Exits	-30	-7.5	-1.0	-4.9
	(7)	(2.2)	(0.2)	(1.4)
p-value	0.41	0.66	0.24	0.97
R^2	0.24	0.23	0.27	0.16
# HSAs	804	804	804	804
# Observations	21,489	21,489	21,489	21,489

Dependent Variable:	Mortality					
	Total per 100,000	Amenable per 100,000	AMI per 100,000	Total per 100,000	Amenable per 100,000	AMI per 100,000
	In Counties			In Health Service Areas		
Number of Hospitals + First Lag:						
Net Entries	1.91	2.53	0.29	-0.54	1.70	0.63
	(1.97)	(1.77)	(0.72)	(1.42)	(1.06)	(0.47)
Net Exits	-0.30	-0.26	0.18	-0.45	-0.42	0.05
	(0.28)	(0.29)	(0.08)	(0.21)	(0.21)	(0.08)
p-value	0.42	0.20	0.51	0.47	0.22	0.15
R^2	0.0010	0.0009	0.0005	0.0010	0.0008	0.0004
# HSAs	783	783	783	805	805	805
# Observations	4,243,041	4,243,041	4,243,041	4,390,609	4,390,609	4,390,609

Note: Data cover the 1982-2010 period. The unit of observation is a health service area-year for the quantity outcomes and county-race-gender-age group-year for mortality. Numbers reported in the net entry and net exit rows are the sum of the coefficients on net hospital entry and its first lag (for net entry) and net hospital exit and its first lag (for net exit) from regressions of changes in each of the dependent variables on the increase in the number of hospitals (in health service areas or counties) and its first lag if there is net entry, the absolute value of the decrease in the number of hospitals and its first lag if there is net exit, health service area fixed effects, state-year fixed effects, and demographic and economic activity controls. The mortality specification includes state-year fixed effects and economic activity controls. All regressions are population weighted. The $p-value$ is from a test of the equality of the net entry and the absolute value of the net exit coefficients. Standard errors, in parenthesis, are clustered by health service area.

Table 3: Effect of Exits on Quantity and Mortality in Areas where the Impact is Likely to be Larger

	Utilization					
Dependent Variable:	Cost per capita	Inpatient Days per 1,000	Admissions per 1,000	ER Visits per 1,000		
	In Health Service Areas					
Rural Areas						
Net Exits	-247	-71.2	-8.1	-22.5		
	(46)	(26.9)	(1.6)	(15.0)		
Distance to Hospital>33 Percentile						
Net Exits	-19	-5.0	-0.8	-6.8		
	(11)	(2.3)	(0.3)	(2.0)		
Concentration>33 Percentile						
Net Exits	-62	-15.9	-2.3	-15.6		
	(13)	(4.1)	(0.6)	(3.0)		
	Mortality					
Dependent Variable:	Total per 100,000	Amenable per 100,000	AMI per 100,000	Total per 100,000	Amenable per 100,000	AMI per 100,000
	In Counties			In Health Service Areas		
Rural Areas						
Net Exits	0.40	1.32	3.90	8.52	5.52	1.13
	(12.30)	(10.23)	(4.89)	(7.55)	(7.66)	(2.93)
Distance to Hospital>33 Percentile						
Net Exits	1.07	0.98	-0.36	1.02	0.26	-0.06
	(0.86)	(0.74)	(0.21)	(0.68)	(0.58)	(0.18)
Concentration>33 Percentile						
Net Exits	3.97	2.21	0.58	2.75	2.68	0.32
	(1.53)	(1.58)	(0.56)	(1.08)	(1.04)	(0.41)

Note: Data cover the 1982-2010 period. Rural sample is limited to health service areas where its constituent counties have urban populations<20,000 and do not border metro areas. The unit of observation is health service area-year for the quantity outcomes and county-race-gender-age group-year for mortality. Numbers reported in the net exits rows are the sum of the coefficients on net hospital exit and its first lag from regressions of changes in each of the dependent variables on net entry (in health service areas or counties), the number net exits (in health service areas or counties), the first lag of both entry/exit terms, health service area fixed effects, state-year fixed effects, and demographic and economic activity controls. The distance and concentration specifications report the interaction of indicators for values above 33 percentile of the concentration or distance distributions with the net entry and exit variables and include interactions of indicators for values below 33 percentile with the net entry/exit in variables as controls. Distance is the distance from the entering/exiting hospital to the closest hospital. Concentration is the HHI in the health service calculated with admissions as if each hospital is independently owned. The mortality specification includes state-year fixed effects and economic activity controls. All regressions are population weighted. Standard errors, in parenthesis, are clustered by health service area.

Table 4: Lives Saved per Unit of Health Care from Marginal Hospitals

	Lives Saved per			
	$1 Million of Hospital Costs		Admission	
Full Sample				
Net Entries	0.104		0.002	
	[-0.633	1.911]	[-0.013	0.028]
Net Exits	-0.150		-0.005	
	[-0.393	0.047]	[-0.013	0.002]
Rural Areas				
Net Entries	0.021		0.000	
	[-8.689	0.997]	[-0.055	0.022]
Net Exits	0.344		0.011	
	[-0.316	1.151]	[-0.010	0.034]
Distance>33 Percentile				
Net Entries	0.151		0.004	
	[-1.466	1.965]	[-0.023	0.044]
Net Exits	0.523		0.013	
	[-0.294	5.745]	[-0.003	0.060]
Concentration>33 Percentile				
Net Entries	0.011		0.000	
	[-1.276	2.896]	[-0.014	0.026]
Net Exits	0.445		0.012	
	[0.106	1.058]	[0.003	0.034]

Note: The point estimate in the full sample rows is computed by taking -1 times the ratio of the health service area mortality and the health service area hospital costs estimates from table 2 times $1,000,000/100,00 or health service area mortality and the admissions estimates from table 2 times 1,000/100,000. The point estimate and confidence interval in the Rural Areas, distance rows, and concentration rows are computed using the same procedure using table 3 and the online appendix 2. The confidence interval, in brackets, is computed by block bootstrapping over health service areas using 1,000 iterations.

Table 5: Effect of the Closest Hospital's Entry and Exit on Medicare Beneficiaries

Dependent Variable:	Total	Acute Hospital					
	Expenditures	Expenditures	Days	Admissions	ER Visits	Mortality	AMI Mortality
	per capita	per capita	per 1,000	per 1,000	per 1,000	per 100,000	per 100,000
Number of Hospitals + First Lag:							
Net Entries	96	31.8	4.2	7.5	39.2	115.1	-25.6
	(55)	(32.1)	(10.5)	(2.3)	(6.6)	(61.3)	(13.0)
Net Exits	-32	-35.8	-19.8	-8.3	-19.4	51.7	-1.6
	(51)	(25.2)	(11.4)	(2.0)	(3.0)	(76.4)	(17.8)
R^2	0.04	0.04	0.04	0.04	0.05	0.09	0.08
# HSAs	805	805	805	805	805	805	805
# Observations	30,393,000	30,393,000	30,393,000	30,393,000	25,523,793	30,393,000	22,434,951

Note: Data cover the 1999-2011 period except for ER Visits which are from 2001-2011 and AMI Mortality which is available from 1999-2008. The unit of analysis is the cohort-race-sex-zip code-county-year. Numbers reported in the net entries and net exits rows are the sum of the coefficients on net hospital entry and its first lag (for net entry) and net hospital exit and its first lag (for net exit) from regressions of changes in each of the dependent variables on the increase in the number of hospitals and its first lag if there is net entry, the absolute value of the decrease in the number of hospitals and its first lag if there is net exit that affects the distance to the closest hospital, economic activity controls, and state-year fixed effects. The regressions are weighted by the number of Medicare beneficiaries in each bin. Standard errors, in parenthesis, are clustered by health service area.