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"DOES HIGHER HOSPITAL QUALITY SAVE LIVES? THE ASSOCIATION BETWEEN" "COVID-19 DEATHS AND HOSPITAL QUALITY IN THE USA

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Keywords: COVID-19, County-level Deaths, Hospital Quality, Health Care Systems, Minorities

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Does Higher Hospital Quality Save Lives? The Association between COVID-19 Deaths and Hospital Quality in the USA*

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July 17, 2020

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1 Introduction

The most severely ill patients with COVID-19 require hospital care and, in particular, the care of intensive care facilities and specialists in respiratory medicine. Yet there has been little research to date that has examined the relationship between deaths from COVID-19 and the quality of hospital care in the USA at the spatial level. Some studies of the correlates of cases of, and deaths from, COVID-19, account for some aspects of quantity (e.g. ICU beds, Knittel and Ozaltun, 2020) and access to care (e.g. proportion of the population who have health insurance, McLaren, 2020), but in general there has been little focus on hospital quality.

In this paper, we examine the relationship between the quality of hospital care and mortality from COVID-19 at the county-level. To measure the quality of hospital care, we use quality measures derived from the flagship Hospital Readmission Reduction Program [HRRP] (part of the Affordable Care Act push for pay-for-performance). The program applies financial penalties to hospitals that are deemed to have lower quality, as measured by higher than expected readmission rates for three key conditions: heart attacks [AMI], heart failure [HF], and Pneumonia [PN]. As COVID-19 is a respiratory illness we derive a measure of quality of care that is based on readmission rates for pneumonia.[1] We also derive a pooled measure based on all three of the penalized conditions. Our measures are based on the published excess (risk-adjusted) readmission rates. We further adjust these to overcome issues in using the risk-adjusted rates: we allow for differences in area-level socioeconomic factors which may affect the rates, we correct for the influence of low volumes on the precision of the rates and we derive a measure that allows for the fact that some hospitals are never penalized whilst others always are (details are provided in Section 2.2 below).

We make several contributions to the limited literature that assesses the role the healthcare system plays in determining cases and deaths from COVID-19 in the USA at the spatial (county) level. First, we argue that measures at the county-level of quality of healthcare are not the appropriate measure of quality of hospital care, either in general or for emergency patients with COVID-19. Most health research that has focused on quality of hospital care examines hospital referral regions (HRR) as these are based on the travel patterns of individuals who have emergency care (ambulance referrals). These frequently cross county lines (Chandra et al., 2016). We, therefore, use a measure which uses hospital referral region variation in quality which we map to the county-level based on zip-code exposure to HRRs.[2] This is used as a measure of quality of care at the county-level, but we also show our results are robust to measuring quality at the higher HHR level. Second, we use two measures of quality of care, one of which focuses on treatment of a respiratory condition (pneumonia) and one of which examines quality of care at the hospital level by combining quality measures for all three penalized conditions. This allows us to distinguish between general hospital quality and quality in treatment of respiratory infection. Third, we control for the many factors at the county-level that have been shown to be associated with the spread of the virus (as measured by confirmed cases, and also control directly for cases as well). Finally, given the large volume of papers showing a differential number of cases and deaths in minority

[1]Most people who get COVID-19 have mild or moderate symptoms such as coughing, a fever, and shortness of breath. But a subset of individuals who catch it develop severe pneumonia in both lungs e.g. https://www.webmd.com/lung/COVID-and-pneumonia#1.

[2]That the spatial level of analysis is important in this setting is not only suggested by the large academic literature, but also by recent reports of referrals of COVID-19 patients between capacity-constrained hospitals, e.g. https://www.chron.com/local/article/Brink-of-capacity-Houston-hospitals-now-15380502.php.

populations, we explicitly examine the interaction between quality of care and minority population shares in the county (Williams and Cooper, 2020).

To motivate our approach, Figure 1 shows the spatial association between our measure of the quality of hospital care and the number of deaths from COVID-19 between January 22, 2020 to June 28, 2020 at county-level for the USA. The figure shows substantial variation in both the measure of hospital quality and death rates across counties, but also shows considerable overlap between lower hospital quality (darker shading in Panel A) and higher death rates (darker shading in Panel B). While suggestive of a relationship this correspondence could, of course, be driven by many other factors. Our analysis controls for a large set of these. We find, after controlling for this large number of possible confounders at the county-level and including state fixed effects, our measure of hospital quality based on excess (risk-adjusted) readmissions from pneumonia admissions in the hospital referral network correlates strongly with higher death rates at the county-level. We also find quality based on readmissions for all three penalized conditions is associated with deaths, but this is a less strong association. We show that the measures of quality of care are not predictive of cases of COVID-19 after accounting for possible county-level confounders and state fixed effects, meaning that we can control for cases in our analysis. We find no association between health of the population (as measured by the population mortality rate for any of the conditions: AMI, HF, PN), hospital availability or HRR-level market concentration, and COVID-19 deaths.[3] This suggests that what we isolate is a local hospital quality effect.

Finally, we document an important heterogeneity in the relationship between health care system and the mortality rate. Specifically, we find that health care quality has highly heterogeneous effects by share of minority populations in the county. In the highest minority areas, health care quality has no association with death rates. However, the protective impact increases monotonically as the share of minorities in the county population falls. This gap in the protective effect of quality appears relatively early in the pandemic and increases over time.

The paper is structured as follows. We first survey the relevant literature, with a focus on identifying potential confounders at the county-level. In Section 2 we discuss how we assign hospital referral region quality to counties, how we measure quality, the data we use, and our empirical specification. In Section 3 we present our results. Section 4 discusses our findings.

1.1 Relevant literature

The literature on factors associated with the spread of, and deaths from, COVID-19 is large and growing (an early review is Brodeur et al., 2020a). Here we discuss papers that have focused on cases and/or deaths from COVID-19 at a spatial level (in the US generally the county). These have examined a large range of factors, including demography and socio-economic and health status of the population; the level and type of economic activity in communities and the associated mobility patterns; the local physical environment (pollution, climate); and social attributes of the local community (social cohesion, trust). Our analysis of the impact of the quality of hospital care on deaths at county-level therefore needs to control for these factors.

Individual characteristics associated with the risk of death from COVID-19 are studied in de Lusignan et al.

[3] See Desmet and Wacziarg (2020) and Knittel and Ozaltun (2020) who examine the first two of these confounders.

(2020), using a large UK population-based sample. A large set of risk-factors including age, ethnicity, and other health conditions are identified. Individual characteristics associated with the risk of death from COVID-19 symptoms are studied in Wiemers et al. (2020), who show large socio-economic disparities. Borjas (2020) finds that the share of people residing in immigrant populations is predictive of death rates in New York. Williams and Cooper (2020) discuss potential roles for racial segregation in cases and deaths from COVID-19. Schmitt-Grohé et al. (2020) find difference in the the probability that the test result is negative between rich and poor zip-codes in New York.

The impact on cases/spread of mobility patterns and of measures to decrease mobility have been widely studied. Brodeur et al. (2020b), Friedson et al. (2020), Sen et al. (2020) and Dave et al. (2020) examine stay-at-home orders, Courtemanche et al. (2020) strong social distancing measures and Barrios et al. (2020) variation in civic capital. Papageorge et al. (2020) assess risky and health behaviors at the county-level and Chan et al. (2020) provide evidence that county-level risk attitudes are important. Softer policy measures such as mask-wearing are assessed in (Bursztyn et al., 2020; Chernozhukov et al., 2020). County-level social capital and mobility in the US are examined in (Borgonovi and Andrieu, 2020; Ding et al., 2020) and in Germany (Glogowsky et al., 2020).

Despite the large volume of studies, whether and how COVID-19 deaths are related to the health care system is less explored. A small number of studies have identified persistent spatial correlates of health care quality. Lin and Meissner (2020) find "strong persistence in public health performance in the early days of the COVID-19 pandemic. Places that performed poorly in terms of mortality in 1918 were more likely to have higher mortality today." Christensen et al. (2020) examine a developing country and conclude that "[u]nderuse of health systems and a lack of confidence in their quality contribute to high rates of mortality". Health insurance as well as health care quality may also be expected to be a mediating factor in the pandemic severity. Clay et al. (2020) note that cross-state variation in mandated eligibility for Medicaid is highly correlated with two influenza pandemics — the 1957-58 "Asian Flu" pandemic and the 1968-69 "Hong Kong Flu" — that arrived shortly before and after the program's introduction.

Three recent papers are most comparable in statistical approach to the present paper. Desmet and Wacziarg (2020) focus on the growth in deaths from March 15, 2020 to May 26, 2020. They measure the county-level quality of healthcare using the risk-adjusted 30-day mortality rates for heart attacks, heart failure, and pneumonia. They find no robust correlation between any of these and the growth in deaths. Knittel and Ozaltun (2020) examine the death rate using county-level data from April 4, 2020 to May 27, 2020, focusing on four sets of variables: county-level socioeconomic variables; modes of commuting; county-level health variables; and climate and pollution patterns. They find that death rates are not correlated with local pollution, obesity rates, ICU beds per capita, or poverty rates. McLaren (2020) examines death rates, focusing on racial disparities. Minority population shares are found to be strongly correlated with total COVID-19 deaths but for Hispanic/Latino and Asian minorities those correlations are fragile and largely disappear after controls for education, occupation, and commuting patterns. For African Americans and First Nations populations the correlations are very robust. However, the racial disparity does not seem to be due to differences in income, poverty rates, education, occupational mix, or - importantly to this paper - access to health care.

2 Estimation strategy and data

Our aim is to examine the association between the county-level death rate per 10,000 persons and the quality of care at county-level. To do this, we need to address two issues. First, while death rates are collected at county-level, measures of hospital quality at the county-level do not take into account the fact that travel patterns for hospital care frequently cross-county borders. Most health system research in the USA focuses on hospital referral regions (HRR). These are based on the network of ambulance referrals and cross county lines (for example, Chandra et al., 2016; Wennberg and Cooper, 1998). Given that capacity-constrained hospitals refer COVID-19 patients to nearby hospitals, these referrals are highly likely to be driven by ambulance referral patterns. Therefore quality measured at the HRR level is the relevant level for our analysis and so we need to assign measures of quality at the HRR level to each county. Second, we need to choose a measure of hospital quality. We seek a medium-term measure that is not driven by year on year variation that may reflect noise. We begin by describing how we assign hospital quality measured at HRR level to a county and then describe the measure of quality we use.

2.1 Assigning a HRR measure to the county-level

To assign quality measured at the HRR level to each county we use a simple weighted-average approach. First, we classify a HRR as the average quality μ_{hrr} of the hospitals it covers. Second, we assign to each county c a weighted average of the quality exposure equal to the fraction of the zip-codes that belong to the referral network.[4] Weights are the number of zip-codes i in a county that merge into a HRR, divided by the total number of zip-codes in the county. More specifically,

$$\text{quality}_{c_{hrr}} = \sum_i \frac{\#\text{zip}_{i_{hrr}}}{\sum \#\text{zip}} \mu_{hrr}. \tag{1}$$

For example, *Autauga County* comprises of 13 zip-codes, 4 of which belong to HRR Birmingham and 9 to HRR Montgomery, with average hospital quality of .66 and .72, respectively (higher numbers refer to worse quality). Thus the assigned weighted quality exposure is simply .70. This places *Autauga County* in the 62.94 percentile of the county quality distribution, which has a mean of 0.629 and a standard deviation of 0.12.

In a robustness check, we calculate quality exposure as the simple average of all HRRs a county has ties to without weighing by how many zip-codes in a county belong to a HRR. In this case, *Autauga* would have a quality of $(0.66 + 0.72)/2 = 0.69$,[5] We refer to the first approach as "zip-weighted" and the second as "equally-weighted" quality exposure.[6]

[4] We merge counties, using the United States's Federal Information Processing Standards [FIPS], to zip-codes (Source: https://data.world/niccolley/us-zipcode-to-county-state, accessed, 16 April 2020) and zipcodes to HRRs (Source: https://atlasdata.dartmouth.edu/static/supp_research_data#crosswalks, accessed, 16 April 2020). Almost all counties are located in two or more HRRs.

[5] The equally weighted approach would place *Autauga County* at the 62.84 percentile of the quality distribution.

[6] Another approach would be to use the zip-code level death rates. While at the zip-code level there is a unique correspondence to HRRs, zip-code death rate is not yet available at scale. Moreover, given the movement of patients across areas due to the disruptive effects of COVID-19 on hospitals, HRRs are the more appropriate level at which assignment to hospital takes place.

We average across hospitals within a given HRR to μ_{hrr}, and use equation (1) to calculate exposure at the county-level.

2.2 HRR-level quality measure

We now describe our measure of medium-term HRR quality μ_{hrr}, and variations thereof. Our measure is based on the publicized annual penalty status of hospitals due to excess pneumonia readmissions. Readmissions for emergency conditions are frequently used as a measure of hospital quality (e.g. Gaynor and Town, 2011). From 2012 onwards Medicare has reduced reimbursements to hospitals if, in a three year period their (risk-adjusted) excess readmission ratio in one of three emergency conditions (pneumonia, AMI and HF) was larger than one, i.e. the hospital had more readmissions than the average hospital with a similar case-mix (McIlvennan et al., 2015).

Risk-adjusted readmissions may not measure latent quality if there is patient selection by the patient (Doyle et al., 2015) or the hospital (Gupta, 2017). However, as the measure is based on admissions for emergency conditions, there is limited scope for self-selection (Chandra et al., 2016). It has been shown that the published simple measures predict (increases in) market share (Chandra et al., 2016), are highly correlated with other important measures of hospital quality (Kunz et al., 2020) and have been further been validated by Doyle et al. (2019).[7]

In our context, patient and hospital selection is possibly less of a concern since we aggregate average quality of hospitals to the HRR level. However, as the official Centers for Medicare & Medicaid Services [CMS] risk-adjustment is only performed based on age, sex, and co-existing conditions, we further risk-adjust for local socio-demographic variation by extracting a medium-run measure of quality using a panel fixed effect approach over the financial years 2012-2016. Details are provided in Kunz et al. (2020) but in brief, Kunz et al. (2020) derive a (condition)-hospital specific measure of medium-run quality from longitudinal observations of the penalty status. Unlike the penalty status which is either one or zero (and for many hospitals is either one or zero for every year they are observed), this approach provides a quality estimate for every hospital that is observed over time. Further adjustments are undertaken which means the measure is not plagued by regression-to-the-mean and is automatically shrunken towards a no-quality benchmark. This approach provides a parsimonious way to classify the median-term quality of a hospital.[8]

In an assessment of the association of quality with death rates from COVID-19, it is important to account for the availability of hospitals (Knittel and Ozaltun, 2020) and access to local primary health care (commonly measured by the number of admissions for ambulatory sensitive conditions (Gu et al., 2014)). We also control for the hospital concentration at the HRR level (measured by the Herfindhal-Hirshman Index [HHI], see Kunz et al. (2020). We use the same weighting approach as for our quality measure to assign these to the county-level.

While we use a measure based on the readmission rates used to measure quality by Medicare, we undertake

[7] Other corrections for patient selection include Hull (2016) and Geweke et al. (2003).

[8] Kunz et al. (2020) show that this measure correlates within hospitals across the three penalized conditions and across hospitals with overall readmissions, mortality rates, and patient satisfaction, all measures which have been used to assess hospital quality of care. More details on the fixed effects estimation procedure can be found in Kunz et al. (2018).

several tests to show that our main conclusions do not hinge on our precise measure of quality. First, we derive the medium-term measure of quality for all the three penalized conditions (AMI, HF, and PN) and average this. The association of this pooled hospital measure exhibits a much less precise association with county-level deaths, which is what we would expect given that COVID-19 is a respiratory condition. Second, we also show results using the average for 2011-2015 of the CMS's excess readmission ratios (i.e. the measure on which Medicare bases its annual reimbursements to each hospital). The results are, if anything, stronger using this measure rather than our derived marginal penalty propensity (Appendix Table 3). However, as this readmission rate does not account for the regional variation in demographics or for noisiness of low rates, we use our preferred more conservative measure, which does adjust for such influences.

Finally, we measure quality as the average 30-day mortality rate for pneumonia for 2011-15, using the same weighted-HRR method to derive the county-level measure (Appendix Table 3).[9]. Confirming Desmet and Wacziarg (2020), we find no association between COVID-19 deaths and (prior) mortality rates from pneumonia. This null finding addresses concerns that our results of an association with quality as measured by pneumonia readmissions could be driven by a potential correlation between the respiratory health of the patients treated within a HRR and deaths from COVID-19.

2.3 Outcomes measures

Our main outcome is the cumulative county-level deaths per 10,000 individuals. The data is provided by the Centers for Disease Control and Prevention [CDC], state- and local-level public health agencies and has been aggregated by USAfacts, downloaded on June 28, 2020 and reflects the numbers since January 22nd, 2020. This measure of deaths is based on directly observed deaths as explained and motivated by Aliprantis and Tauber (2020).[10] We also examine cumulative confirmed cases, from the same source and defined analogously. We examine these to assess whether our quality measure is measuring quality. If hospital quality is predictive of cases, it may indicate that we are not identifying only hospital quality but have a measure that is correlated with the underlying conditions that also affect the spread of the virus.

2.4 Empirical specification

We estimate simple cross-sectional OLS models of the association of HRR quality with COVID-19 deaths at June 28, 2020:

$$y_c \quad = \quad \alpha + \tau \text{quality-exposure}_{c_{hrr}} + x_c' \beta + z_{c_{hrr}}' \gamma + \delta_s + \varepsilon_c, \tag{2}$$

where y_c are deaths in county c divided by population $pop_c/10,000$, the covariate vector x contains county-level and $z_{c_{hrr}}$ HRR-weighted level correlates, δ_s state fixed effects and ε_c error term, we use robust standard errors

[9]For both the direct excess readmission ratio as well as the mortality rate measure we use pneumonia only as well as the pooled (AMI, HF, PN) and both the zipcode weighed and equally weighted approaches

[10]Until April 14, 2020 [84 days after the first death in the data], only the disease death – deaths in a hospital accompanied by a positive COVID-19 test – were counted as deaths. After that date, the US counted disease death which includes both confirmed and probable deaths (Aliprantis and Tauber, 2020).

throughout.

The main concern in estimating the spatial correlation between hospital network quality and county-level death rates is the presence of omitted variables that correlate with both the death rate and weighted quality. We take several steps to overcome this. First, as noted above, our measure of hospital quality is the fixed effect extracted from measures for the years 2011-2015 after accounting for several potential determinants of quality of healthcare, at the hospital, county, and HRR-level. This is determined before the onset of the COVID-19 pandemic. Second, we include a large set of controls at the county-level that have been discussed in previous research (see Section 1.1) on the association between cases or death and county-level characteristics (our empirical measures are detailed below in Section 2.5). Third, we include state fixed effects to control for the differential policy responses at the state-level (Knittel and Ozaltun, 2020). Finally, we show that the quality of hospital care is not predictive of the number of cases.

We also examine the heterogeneity of the effect of the quality of healthcare across the minority population composition of the county (e.g. McLaren, 2020; Williams and Cooper, 2020). We classify counties by the size of their minorities into four quartiles Q and estimate the following specification

$$y_c \quad = \quad \alpha + \sum_q \tau_q \text{quality-exposure}_{c_{hrr}} \times 1(\text{minority share}_c < Q^q) + x_c'\beta + z_{c_{hrr}}'\gamma + \delta_s + \delta_Q + \varepsilon_c, \qquad (3)$$

where we include both indicators for whether the county has a high share of minorities (lowest quartile) to low share (highest quartile) δ_Q and their interactions of quartile indicators $q = 1, ...4$ with our quality measure.[11]

As our primary outcome is the cumulative deaths on the 28th of June, this focus might hide important dynamic adjustments over the course of the pandemic. For example, hospital quality may have been predictive of deaths early on in disadvantaged areas (perhaps due to less funding) but as the federal response supported less equipped referral regions, the differential effect may have fallen over time. We therefore also assess how any quality gap by minority population composition evolved throughout the pandemic until the June 28, 2020. We estimate equation (3) separately for every day since the first death in the data Knittel and Ozaltun (see also 2020). This also addresses the change in the death definition used by the US on day 84.

2.5 Control variables

At the county-level, we include a large number of local controls, summarized in Appendix Table 1.[12] These are measures of economic situation (all ages percent poverty and median household income); measures of community health, including the population share in poor or fair health, population life expectancy and premature deaths; share without health insurance (access); share flu vaccinate (awareness of risks of contagious diseases); population adult smoking and air pollution (argued to exacerbate risks of poor outcomes from COVID-19); commuting patterns (driving alone to work and having a long commute to capture public transportation); res-

[11]The quartiles are based on (1-population share of non-Hispanic whites). We additionally control for the shares of Hispanics, non-Hispanic Blacks, and other minorities.

[12]For a small number of variables and counties, information on some covariates are missing. We recode them as zero and include an indicator for missing values of the covariate. Our results are not driven by this approach: see Appendix Table 3.

idential racial segregation; measures of local social capital; population measures including population density, average household size, households 65 and older living alone, share age 65 and older, shares of different education compositions, and share foreign-born.[13] At the HHR level we include the availability of hospital care, hospital market concentration, and the accessibility of local primary health care.

3 Results

We start by presenting descriptive associations between our constructed measure of county hospital quality exposure and the cumulative death rate from COVID-19.

Figure 2 shows the raw association of the zip-weighted HRR quality measure and deaths per 10,000 people in a county in Panel A, and the average quality in one hundred percentile bins in Panel B. Going from the best hospital referral regions (lowest percentile) to the worst raises the average deaths from approximately 1 in a thousand to more than 2 in a thousand. This simple bivariate relationship shows a strong association between access to high-quality (in treatment of respiratory conditions) hospitals and the death rate from COVID-19.

Figure 3 presents the evolution of deaths and cases over time, distinguishing between high and low health care quality counties (counties split at the median of our quality measure). Counties classified using these pre-existing quality measures show a starkly different evolution over time. Separating the counties into high-quality and low-quality exposure (at the median) results in a split of 1,645 million people in low-quality exposure counties and 1,637 in high ones, but deaths are much more prevalent in low-quality exposure counties at 83,722 and 40,377 respectively. Even 160 days after the first death, the gap in deaths is still widening between the two groups of counties. In contrast, the numbers of confirmed cases appear to move in parallel across the two groups after a minor divergence at the beginning of the outbreak.

Of course, many factors may explain these unconditional correlations: we address these in Table 1 which presents the results of estimating equation (2). In Column (1) we regress the county's total number of deaths per 10,000 people only on our zip-code weighted HRR quality exposure measure. The unconditional coefficient is very large and highly significant. In Column (2) we include both the state fixed effects as well as the number of cases per 10,000. As expected, as state policies differ, the association falls but remains positive and significant. The mean sample deaths per 10,000 is 1.684. From Column 2 an increase in quality (a decrease in our score) by one standard deviation of 0.12 is predicted to lower the death rate to 1.477, a 12.3 percent reduction.

Our HRR-quality measure level may still pick up market-level factors unrelated to quality, such as the availability of hospitals and the market-level concentration, both of which may be associated with the quality measure. Controlling for these in Column (3) shows that their inclusion neither changes our quality metric estimate nor does either confounder covary with the death rate in a statistically significant way. In Column (4), conditioning on a very large set of potential confounders on the county-level, we continue to find a sizable positive and significant (p-value of 0.065) association between quality of the healthcare system and deaths. An improvement

[13]The inclusion of these should account for confounding between our measure of quality (readmissions for pneumonia treatments) and death rates arising from both being driven by the underlying health of the local population.

in quality by one standard deviation would predict a death rate of 1.531 per 10,000 (a 9.2 percent decrease from the mean).

This average, however, may hide heterogeneity across minority areas. Thus we estimate equation (3) in Column (5).[14] In high minority areas, hospital quality is essentially irrelevant with a standard error larger than the point estimate. But the association between the death rate and the health care system is monotonically increasing as the share of minorities is declining, being highly significant and large in magnitude for the lowest minority areas.[15] Overall the joint p-value of the four interactions confirms the results from Column (4).

In sum, the documented association is very robust, economically meaningful, and survives controlling for state fixed effects, cases, and a very large set of covariates. We test other changes to our specification. In Column (6) we replace our proportional zip-code weighting approach with equally-weighting of each HRR a county is served by (we use the same weighting for the other HRR level covariates). The results are robust, are even larger in the lowest minority regions, and slightly more (jointly) significant. Next, we replace our zip-code weighted pneumonia quality with a zip-code weighted pooled quality measure for all three HRRP penalized emergency conditions (AMI, HF, PN). As expected, as this is not a pneumonia specific measure, the association is smaller and less precisely estimated. The pattern is still monotonically increasing over the minority distribution but the coefficients are neither individually nor jointly significant. We interpret this as evidence that we are showing an association between deaths and hospital quality in the treatment of respiratory diseases. In Column (8), we replace our outcome variable with the number of cases per 10,000 people. Reassuringly, hospital quality does not predict cases.

Finally, we assess the association of quality and deaths over time for counties with different minority shares, estimating model (2) separately for each day. In Figure 4 we plot the coefficients of quality exposure interacted with minority shares for the four quartiles of minority shares. The final coefficients in these plots correspond to the coefficients presented in Table 1, Column (5). Across the four panels A to D, the figure shows the monotonic increase between minority areas. In the 25 percent highest minority share counties (Panel A), health care system quality is not associated with higher death rates. But as the share of minority population falls, the association increases over time and is highly significant throughout for the mainly non-Hispanic white counties (Panel D). The differences between high-quality HHR exposed counties developed early on in the pandemic and somewhat stabilized over time, leaving a persistent gap between high-quality and low-quality HRR exposed counties.

In a further extension, we tested the association between the published measure of excess readmissions used by Medicare to reimburse hospitals and COVID-19 death rates. Table 2 presents these results. In sum, qualitatively identical results are derived using this excess readmission ratio directly. The association is larger and better defined statistically, but as this published measure does not control for differences in socio-demographics at the hospital level, is not adjusted for the uncertainty inherent in measures based on smaller volumes (considered to be important in the literature (e.g. Chandra et al., 2016; Frederiksen et al., 2019), we prefer our adjusted measure.[16] In the same table, we also show that mortality rates from Pneumonia (using data from the same

[14]We include all dummies interacted with quality so can test directly whether any of them is significantly different from zero.

[15]In Appendix Table 4 we present the full set of variables along with descriptives for all covariates included in the model (omitting state fixed effect).

[16]Our choice is confirmed by the significant association between the published measure of quality and the

period as our quality measure) are not predictive of current death rates.

In Table 3 we present further robustness tests of our main specification, Column (5) of Table 1. First, we omit cases of COVID-19 from the set of covariates. This has little effect on the estimate of the impact of hospital quality, which was already suggested from the non-existent correlation, Column (8) of Table 1. Second, we use a log specification rather than deaths per 10,000 (Desmet and Wacziarg (2020)). Third, using deaths as an outcome we also estimate a negative binomial model (as Knittel and Ozaltun, 2020; Wu et al., 2020). Fourth, we assess whether accounting for the death rates in the surrounding areas changes the correlational patterns we observe. To do this, we follow McLaren (2020) by controlling for the leave-one-out of deaths in the state. Finally, we drop all observations with missing values in any of the county-level covariates. None of these tests changes our substantive conclusions.

4 Discussion

This paper examines the association between quality of hospital care and COVID-19 deaths at the US county-level. We find that higher quality of care is associated with lower death rates, controlling for a large set of possible confounders. In addition, we find an interaction with minority population share: the lower the share of minority populations in a county the greater the impact of quality of care. Our results are robust to a number of tests of the specification of quality. Importantly we find no association between recorded cases and quality.

Our analysis is subject to a number of caveats. We are not showing causality, simply robust correlations. There is not consistent zipcode level data on hospital quality, which means we assign hospital quality from the quality of the hospitals in the hospital referral regions used by patients in the county rather than simply of hospitals in the county. However, given travel patterns for emergency care (with respect to which referral regions are defined), quality of hospitals in referral regions would seem to be a more appropriate measure of quality to which the county population has access. The gap between recorded and true cases and deaths from COVID is likely to vary between counties as it will depend on different testing capacities (e.g. Knittel and Ozaltun, 2020). How this might affect our results is not *a priori* clear. However, the fact we find no association between cases, which are primarily hospital diagnosed, and quality should alleviate this concern.

In conclusion, we find hospital quality is associated with lower death rates from COVID-19 at the country level. Our findings of a lower effect of quality on death rates for counties with higher minority shares support recent research drawing attention to the need to improve care in under-resourced settings for vulnerable groups as an important "treatment" for racial disparities in health (Williams and Cooper, 2020).

cumulative number of confirmed cases, which suggests that the risk-adjustment undertaken for the published measures is not sufficient to extract the quality-only variation.

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Figures & Tables

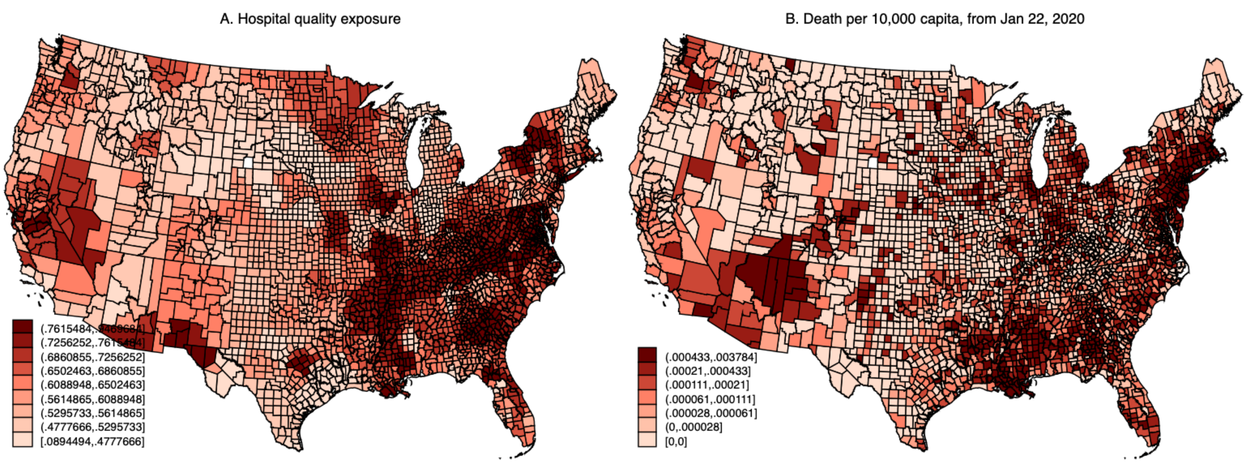

Figure 1: County-level spacial distribution of HRR quality exposure and deaths per 10T population

Note: The map shows in Panel A. our measure of county-level Hospital Referral Region quality exposure, measured from risk-adjusted longitudinal hospital penalty status for readmissions from Pneumonia admissions, and in Panel B. the cumulative number of deaths per 10 thousand population from the 22nd of January 2020 till the 28th of June 2020.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, own calculations.

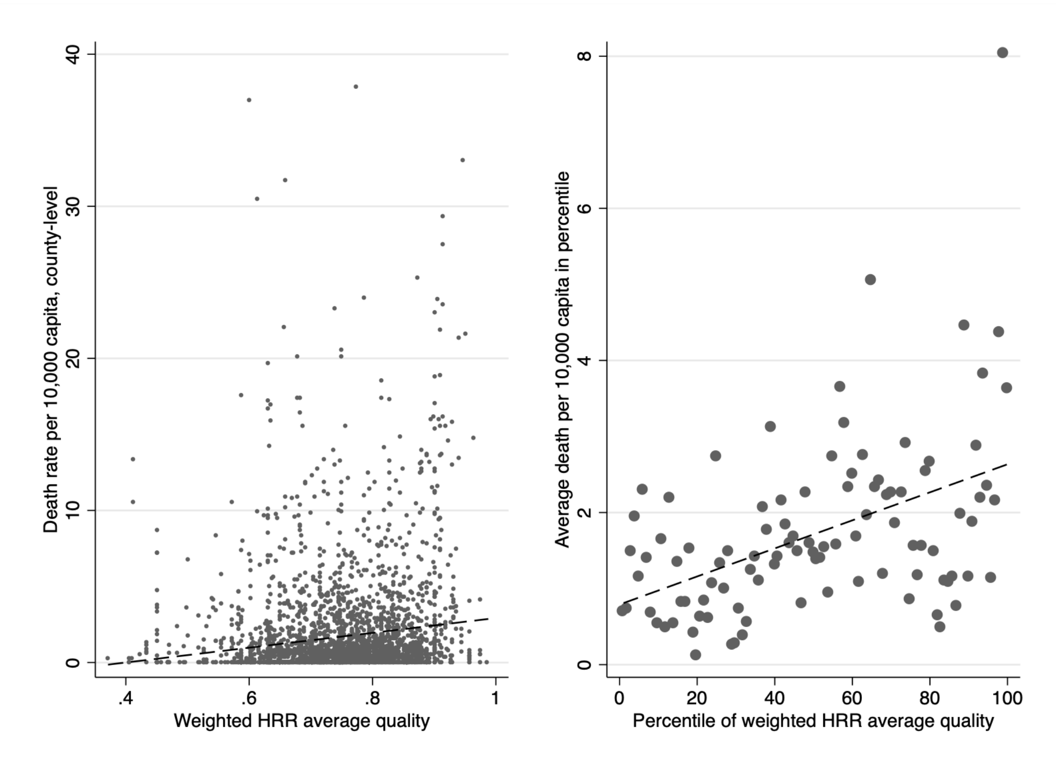

Figure 2: County-level death rate (by 10 thousand people) over excess to HHR-level quality from pneumonia readmissions, raw and in percentile bins

Note: Figure presents association between cumulative death rate per 10,000 people (on the 28th of June 2020) in a county and the counties constructed quality, from equation 1. In Panel A, the raw measure is shown, and in B, the average death across 100 percentile bins. Both include a simple linear fit showing a positive relationship of worse quality (higher values) and more deaths per capita.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, own calculations.

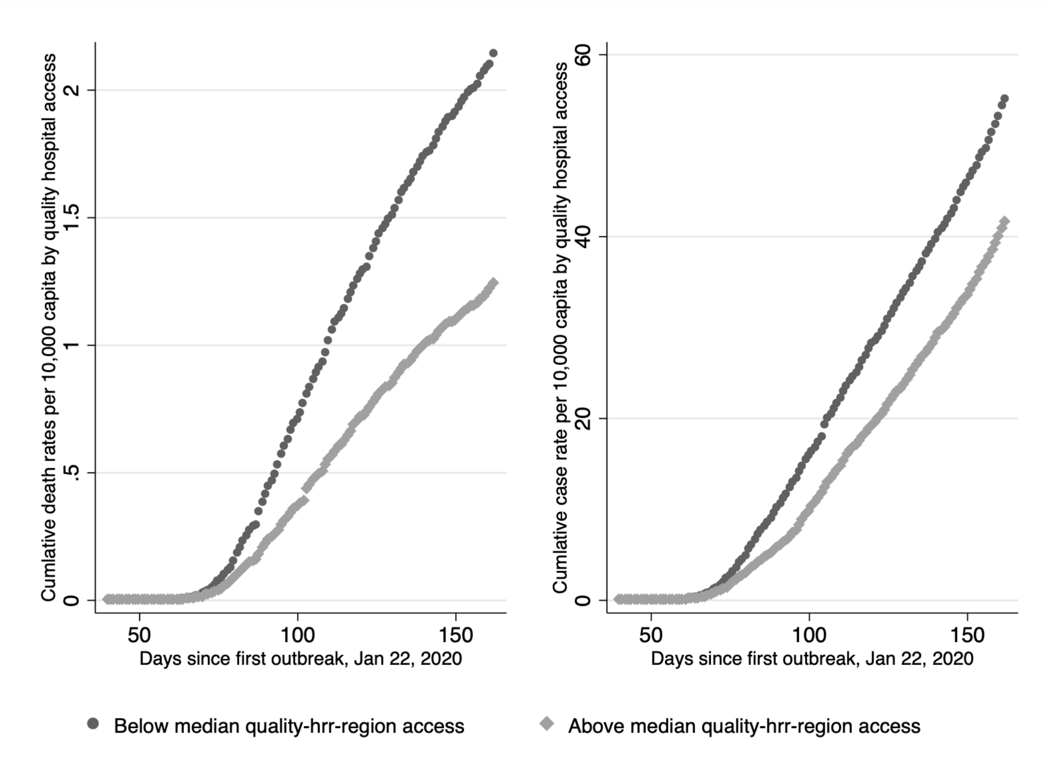

Figure 3: Comparison of death and case rate by 10T population evolution of counties, by median split of high and low-quality access

Note: Figure shows simple cumulative rates of deaths and cases (both by 10 thousand people) from 22 Jan till 28 Jun 2020. The counts are separated by median of our HHR-quality exposure quality metric, there are 1,588 high-quality and 1,552 low-quality counties.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, own calculations.

Table 1: Death rates by access and exposure to quality HRRs

Dependent variables: Deaths and cases by county on 02 Jun 2020	HRR-zip weighted	+ Cases State FE	+ HRR Controls	+ County Controls	+Pop. Shares	Equally weighted	Overall Quality	Outcome Cases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Penalty-extracted quality (patient and socio-demographic risk adjusted)								
quality	4.011	1.731	2.033	1.286				
	(0.564)	(0.754)	(0.790)	(0.697)				
quality × 1st (highest) quart shr minorities					-1.697	-1.573	-3.402	-0.808
					(1.715)	(1.656)	(2.545)	(0.658)
quality × 2nd quart shr minorities					1.015	1.143	0.383	-0.124
					(0.957)	(1.011)	(1.317)	(0.143)
quality × 3rd quart shr minorities					1.268	1.084	1.334	-0.164
					(0.677)	(0.765)	(1.139)	(0.082)
quality × 4th (lowest) quart shr minorities					1.784	2.136	1.514	-0.128
					(0.706)	(0.760)	(1.197)	(0.059)
HHI_{Beds}			0.476	0.983	1.007	0.985	0.889	-0.002
			(0.727)	(0.709)	(0.691)	(0.684)	(0.718)	(0.062)
# Hospitals			-0.005	-0.002	-0.004	-0.004	-0.004	0.001
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.001)
Cases/10,000		2.594	2.631	1.671	1.405	1.422	1.333	
		(0.615)	(0.611)	(0.546)	(0.518)	(0.514)	(0.524)	
Observations	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140
P value joint F-test					0.057	0.048	0.375	0.244
Quality measure								
Zip weighted	✓	✓	✓	✓	✓		✓	✓
Equally weighted						✓		
Condition specific								
Pneumonia specific	✓	✓	✓	✓	✓	✓		✓
Overall specific							✓	
Covariates								
Cases		✓	✓	✓	✓	✓	✓	
State FE		✓	✓	✓	✓	✓	✓	✓
HRR-covars			✓	✓	✓	✓	✓	✓
Cnty-covars				✓	✓	✓	✓	✓
Minority shares					✓	✓	✓	✓

Notes: Table presents OLS coefficients from estimations of equation 2 in Columns 1-4 and 3 in 5-6, and robust standard errors in brackets. In Column (1), the raw correlation is presented, in Column (2) we add state fixed effects and the number of confirmed cases in the county, Column (3) add zip-code exposure weighted measures at the HRR level, number of hospitals, Herfindahl-Hirschman Index (HHI) based on the number of beds, and the number of discharges in ACSC, Column (4) adds a large set of county-level controls, Column (5) adds our indicators and interactions of the quartile in the minority share distribution and population shares of the minorities (Hispanic, non-Hispanic blacks, and non-Hispanic other minorities). Column (6) replaces our HRR level variables with equally weighted averages, (7) replaces the zip-code weighted quality measure with a pooled measure of quality (AMI, HF, and PN). In Column (8) we replace the deaths with cases and use the full specification as in Columns (5)-(7). The joint F-test these all 4 minority share interactions with our quality measure. The descriptive statistics along with the full regression results from Column (5) are presented in Appendix Table 4.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, and others described in Appendix Table 1, own calculations.

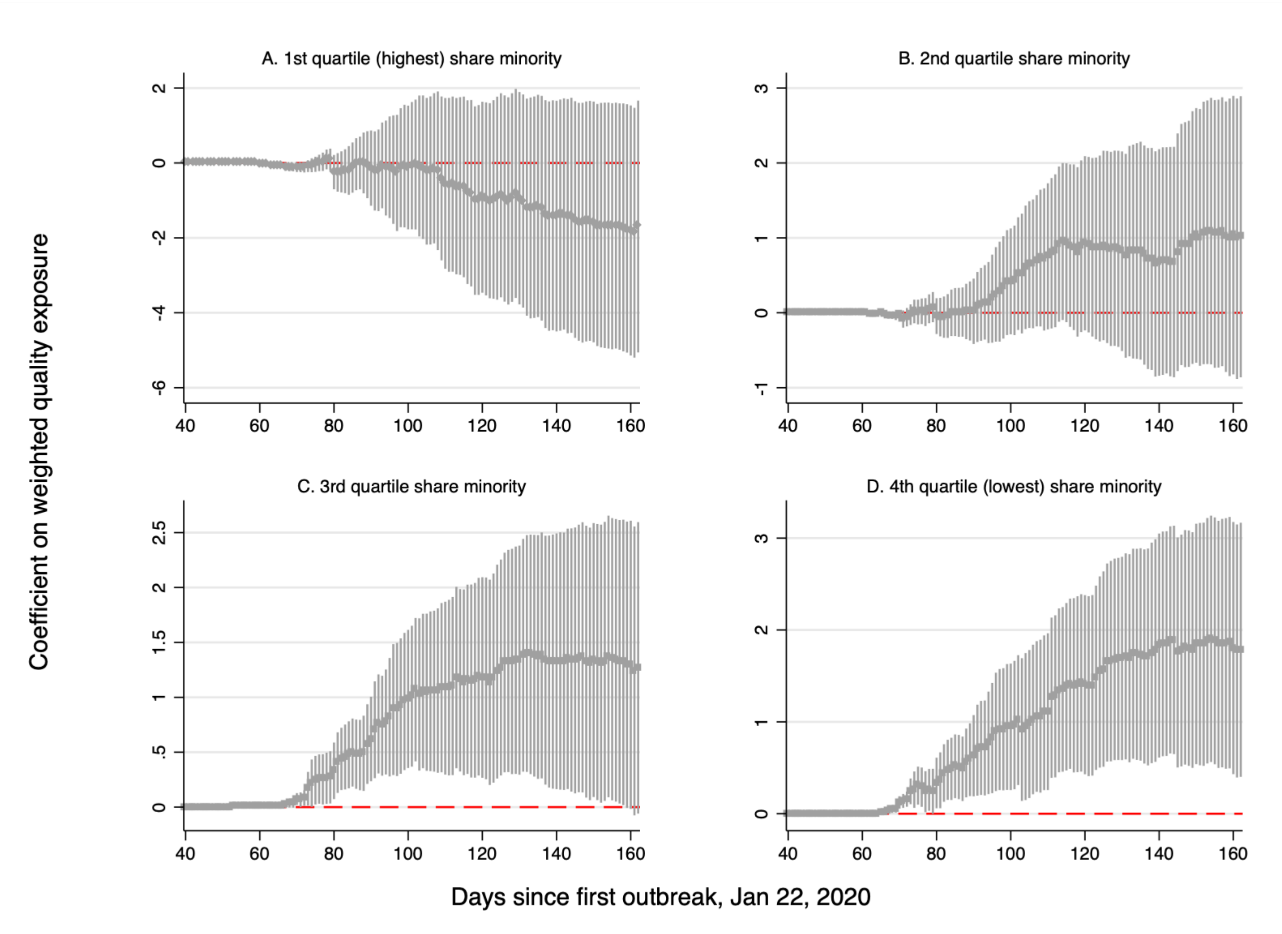

Figure 4: Association between hospital quality exposure and deaths by minority share and over time

Note: Figure plots coefficients from the model (2), and 95 percent confident intervals, of separate regressions for each day since the first death. The regressions are analogous to those in Table 1, Column (5), which is the last point in each of the Panels.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, and others described in Appendix Table 1, own calculations

Appendix: Additional Results

Table 1: COUNTY-LEVEL COVARIATES AND SOURCES

	Value of data	Accessed	Description	N	mean	sd	min	max	
Population	Jun-20	28.06.2020	ACS population estimate	3140	104527.72	333554.61	86.00	10039107.00	link
Percent poverty all ages	Dec-19	14.05.2020	SAIPE, more information see Kunz et al. (2020)	3139	15.14	6.08	2.60	48.40	link
Median household income	Dec-19	14.05.2020	SAIPE	3139	52807.54	13874.79	25385.00	140382.00	
Premature death	2019	02.06.2020	CHI-Project 2019, more information Davis et al. (2020)	3079	8473.41	2697.63	2610.69	35146.65	link
Share poor or fair health	2019	02.06.2020	CHI-Project 2019	3140	0.17	0.05	0.08	0.41	
Poor physical health days	2019	02.06.2020	CHI-Project 2019	3140	3.92	0.71	2.32	6.43	
Poor mental health days	2019	02.06.2020	CHI-Project 2019	3140	3.93	0.61	2.44	5.96	
Share adult smoking	2019	02.06.2020	CHI-Project 2019	3140	0.18	0.04	0.07	0.39	
Food environment index	2019	02.06.2020	CHI-Project 2019	3121	7.47	1.15	0.00	10.00	
Physical in activity	2019	02.06.2020	CHI-Project 2019	3140	0.26	0.05	0.08	0.45	
Excessive drinking	2019	02.06.2020	CHI-Project 2019	3140	0.17	0.03	0.09	0.29	
Alcohol impaired driving deaths	2019	02.06.2020	CHI-Project 2019	3107	0.29	0.15	0.00	1.00	
Share uninsured	2019	02.06.2020	CHI-Project 2019	3139	0.11	0.05	0.02	0.33	
Primary care physicians	2019	02.06.2020	CHI-Project 2019	3006	0.00	0.00	0.00	0.00	
Mental health providers	2019	02.06.2020	CHI-Project 2019	2888	0.00	0.00	0.00	0.02	
Preventable hospital stays	2019	02.06.2020	CHI-Project 2019	3102	4826.99	1862.33	471.00	33333.00	
Flu vaccinations	2019	02.06.2020	CHI-Project 2019	3124	0.40	0.10	0.03	0.65	
Air pollution particulate matter	2019	02.06.2020	CHI-Project 2019	3107	9.02	1.97	3.00	19.70	
Drinking water violations	2019	02.06.2020	CHI-Project 2019	3097	0.39	0.49	0.00	1.00	
Driving alone to work	2019	02.06.2020	CHI-Project 2019	3140	0.80	0.08	0.06	0.97	
Long commute - driving alone	2019	02.06.2020	CHI-Project 2019	3140	0.31	0.12	0.00	0.85	
Life expectancy	2019	02.06.2020	CHI-Project 2019	3071	77.45	2.98	62.59	97.97	
Premature age adjusted mortality	2019	02.06.2020	CHI-Project 2019	3079	406.64	112.57	123.60	1146.10	
Drug overdose deaths	2019	02.06.2020	CHI-Project 2019	1720	21.61	11.64	3.21	111.54	
Residential segregation black white	2019	02.06.2020	CHI-Project 2019	2059	45.39	16.55	0.63	91.12	
Social Capital County-Level Index	Apr-18	29.05.2020	SCI-Project, for more information, see U.S. Congress. (2018)	2990	0.00	1.00	-4.32	2.97	
Community Health Index	Apr-18	29.05.2020	SCI-Project	3137	0.00	1.00	-1.67	7.07	
Institutional Health Index	Apr-18	29.05.2020	SCI-Project	3110	0.00	1.00	-4.66	2.99	
Population density	2010	14.05.2020	Census 2010 for more information, see Kunz et al. (2020)	3140	259.28	1724.94	0.04	69468.42	link
Age 65 and older in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	15.89	4.18	3.47	43.38	
Foreign born in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	4.73	5.71	0.00	53.25	
Ed1 less than highschool in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	13.40	6.34	1.18	66.34	
Ed2 highschool or diploma only in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	34.28	7.18	5.47	55.62	
Ed3 some college in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	21.81	3.88	4.12	38.67	
Ed4 associate degree in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	8.92	2.67	1.12	21.40	
Ed5 college plus in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	21.58	9.43	0.00	78.53	
Average hh size	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	2.52	0.27	1.34	3.97	
Hh 65 plus alone in pct	2010	14.05.2020	Census 2010 - Rural Data Atlas 2021	3140	12.59	3.09	2.78	31.75	
Share hispanic	2018	20.06.2020	ACS for more information, see Knittel and Ozaltun (2020)	3140	18317.61	125582.65	0.00	4893603.00	link
Share nonhispanic white	2018	20.06.2020	ACS population 5 year averages in 2018	3140	62796.26	142875.21	16.00	2659052.00	
Share nonhispanic black	2018	20.06.2020	ACS population 5 year averages in 2018	3140	12648.37	54144.14	0.00	1213706.00	
Share other minority	2018	20.06.2020	ACS population 5 year averages in 2018	3140	9065.94	51033.99	0.00	1749892.00	

Table 2: Death rates by access and exposure to quality HRRs, other quality measures

Dependent variables: Deaths and cases by county on 28 Jun 2020								
	HRR-zip weighted	+ Cases State FE	+ County Controls	+ HRR Controls	+Pop. Shares	Equally weighted	Overall Quality	Outcome Cases
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
A. Raw excess readmission ratio (patient risk adjusted)								
quality	18.408 (1.874)	4.881 (2.239)	8.204 (2.721)	4.327 (2.545)				
quality × 1st (highest) quart shr minorities					-8.831 (6.633)	-6.318 (7.015)	-5.434 (2.292)	3.860 (0.995)
quality × 2nd quart shr minorities					1.973 (3.148)	3.617 (3.235)	-0.853 (1.244)	0.787 (0.395)
quality × 3rd quart shr minorities					4.093 (2.414)	4.540 (2.576)	0.420 (1.006)	-0.221 (0.186)
quality × 4th quart shr minorities					6.021 (2.659)	7.267 (2.883)	1.184 (1.122)	-0.182 (0.172)
HHI_{Beds}			0.316 (0.732)	0.844 (0.702)	0.889 (0.677)	0.888 (0.665)	0.755 (0.684)	0.120 (0.096)
# Hospitals			-0.007 (0.004)	-0.003 (0.004)	-0.004 (0.004)	-0.004 (0.004)	-0.004 (0.004)	0.002 (0.001)
P value joint F-test					0.094	0.089	0.111	0.001
B. Mortality rate (non-risk-adjusted)								
quality	-23.132 (11.264)	19.266 (9.585)	18.729 (9.794)	12.373 (9.309)				
quality × 1st (highest) quart shr minorities					37.396 (21.916)	29.561 (22.243)	3.394 (10.501)	-14.027 (5.343)
quality × 2nd quart shr minorities					-22.669 (12.768)	-24.052 (13.718)	-20.206 (5.981)	-2.966 (1.417)
quality × 3rd quart shr minorities					-6.886 (10.475)	-9.513 (11.484)	-6.748 (4.972)	-0.385 (1.315)
quality × 4th quart shr minorities					8.385 (9.583)	2.346 (10.360)	0.442 (4.658)	-0.208 (1.052)
HHI_{Beds}			0.144 (0.756)	0.779 (0.709)	0.962 (0.693)	0.922 (0.693)	0.847 (0.696)	0.037 (0.087)
# Hospitals			-0.006 (0.004)	-0.002 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.004 (0.004)	0.001 (0.001)
P value joint F-test					0.060	0.121	0.008	0.011
Observations	3,140	3,140	3,140	3,140	3,140	3,140	3,140	3,140
Quality measure								
Zip weighted	✓	✓	✓	✓	✓		✓	✓
Equally weighted						✓		
Condition specific								
Pneumonia specific	✓	✓	✓	✓	✓	✓		✓
Overall specific							✓	
Covariates								
Cases	✓	✓	✓	✓	✓	✓	✓	
State FE		✓	✓	✓	✓	✓	✓	✓
HRR-covars			✓	✓	✓	✓	✓	✓
Cnty-covars				✓	✓	✓	✓	✓
Minority shares					✓	✓	✓	✓

Notes: Table presents robustness to Table 1, see notes there in. We only vary the quality measure in Panel A. to the (raw) averaged excess readmission ratio in Pneumonia (with the exception in Column (7), that uses AMI, HF and PN) provided by CMS, and in Panel B. raw averaged non-risk adjusted mortality rates in Pneumonia everything else is identical to Table 1.

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, and others described in Appendix Table 1, own calculations.

Table 3: Robustness of Table 1

Dependent variables: Deaths and cases by county on 28 Jun 2020

	Basline Col (5), Tab 1	Without Cases	Outcome $log(deaths)$	Negative Binominal	Controlling ROS	Dropping Missings
	(1)	(2)	(3)	(4)	(5)	(6)
quality × 1st (highest) quart shr minorities	-1.697	-2.833	-0.786	-1.632	-3.115	-2.908
	(1.715)	(1.561)	(0.501)	(0.514)	(1.609)	(1.782)
quality × 2nd quart shr minorities	1.015	0.840	0.051	0.008	0.469	0.698
	(0.957)	(0.964)	(0.474)	(0.483)	(0.932)	(0.997)
quality × 3rd quart shr minorities	1.268	1.038	0.597	1.526	1.018	1.414
	(0.677)	(0.683)	(0.481)	(0.514)	(0.657)	(0.901)
quality × 4th quart shr minorities	1.784	1.604	1.588	1.637	1.710	3.394
	(0.706)	(0.710)	(0.546)	(0.716)	(0.692)	(1.196)
HHI_{Beds}	1.007	1.004	0.125	-0.037	1.014	2.153
	(0.691)	(0.692)	(0.356)	(0.412)	(0.678)	(0.981)
# Hospitals	-0.004	-0.003	0.001	-0.001	-0.002	-0.002
	(0.004)	(0.004)	(0.002)	(0.002)	(0.004)	(0.005)
Cases/10,000	1.405		0.652	1.334	-1.647	1.206
	(0.518)		(0.157)	(0.356)	(0.592)	(0.484)
ROS/Mio					-6050.594	
					(1110.471)	
Observations	3,140	3,140	1,935	3,140	3,140	1,987
P value joint F-test	0.057	0.043	0.016	0.000	0.031	0.030
Quality measure						
Zip weighted	✓	✓	✓	✓	✓	✓
Condition specific						
Pneumonia specific	✓	✓	✓	✓	✓	✓
Covariates						
Cases	✓		✓	✓	✓	✓
State FE	✓	✓	✓	✓	✓	✓
HRR-covars	✓	✓	✓	✓	✓	✓
Cnty-covars	✓	✓	✓	✓	✓	✓
Minority shares	✓	✓	✓	✓	✓	✓

Notes: Table presents robustness to Table 1, see notes therein. In Column (1), we represent the baseline estimates from Table 1 Column (5), our main specification. In Column (2), we drop cases from the set of covariates, in Column (3) replace the outcome deaths by 10,000 people to the $log(deaths)$, and in (4) estimate a negative binominal model on the number of deaths. In Column (5) we additionally to Column (1) include the rest of state [ROS] deaths in millions (see McLaren, 2020), and in Column (6) drop all counties that have a missing value in the county-level covariates (there are no other missings in the other variables).

Source: CDC 2020, CMS 2011-2015, Dartmouth Atlas of Health Care, and others described in Appendix Table 1, own calculations.

Table 4: Descriptives and full regression results from Table 1 Column 5, omitting state fixed effects and missing indicators, 1/2

	Descriptives			Regression
		Median Split		
	Mean	High Quality	Low Quality	Tab 1. Col 5
Deaths per 10,000 people	1.685	1.241	2.139	
	(0.061)	(0.065)	(0.102)	
Quality-exposure × 1st quartile share minorities	0.160	0.117	0.204	-1.697
	(0.005)	(0.006)	(0.008)	(1.715)
Quality-exposure × 2nd quartile share minorities	0.156	0.143	0.170	1.015
	(0.005)	(0.006)	(0.008)	(0.957)
Quality-exposure × 3rd quartile share minorities	0.152	0.143	0.162	1.268
	(0.005)	(0.006)	(0.008)	(0.677)
Quality-exposure × 4th quartile share minorities	0.153	0.122	0.184	1.784
	(0.005)	(0.006)	(0.008)	(0.706)
1st quartile share minorities	0.250	0.222	0.279	1.969
	(0.008)	(0.010)	(0.011)	(1.247)
2nd quartile share minorities	0.250	0.263	0.236	0.534
	(0.008)	(0.011)	(0.011)	(0.720)
3rd quartile share minorities	0.250	0.273	0.227	0.284
	(0.008)	(0.011)	(0.011)	(0.434)
4th quartile share minorities	0.250	0.242	0.258	ref
	(0.008)	(0.011)	(0.011)	
Cases/10,000	0.079	0.066	0.092	1.405
	(0.007)	(0.010)	(0.010)	(0.518)
Share Hispanics	0.093	0.123	0.061	-1.262
	(0.002)	(0.004)	(0.002)	(1.365)
Share non-Hispanic blacks	0.089	0.043	0.136	8.194
	(0.003)	(0.002)	(0.004)	(1.923)
Share non-Hispanic other minorities	0.053	0.060	0.045	3.614
	(0.002)	(0.003)	(0.002)	(2.123)
Zip-weighted HHI beds	0.168	0.183	0.152	1.007
	(0.002)	(0.003)	(0.003)	(0.691)
Zip-weighted Nr hospitals	29.805	30.887	28.699	-0.004
	(0.358)	(0.555)	(0.448)	(0.004)
Zip-weighted Discharges ACSC	35.533	32.323	38.818	-0.011
	(0.170)	(0.201)	(0.249)	(0.010)
Poverty Percent All Ages	15.144	14.090	16.223	0.044
	(0.108)	(0.134)	(0.167)	(0.025)
Median Household Income	52,807.538	53,721.461	51,871.813	0.000
	(247.646)	(303.815)	(391.669)	(0.000)
Share Uninsured	0.111	0.120	0.103	-1.660
	(0.001)	(0.001)	(0.001)	(3.369)
Social Capital (County Level Index)	0.005	0.230	-0.213	0.043
	(0.018)	(0.026)	(0.025)	(0.214)
Social Capital (Community Health)	-0.000	0.281	-0.288	-0.197
	(0.018)	(0.028)	(0.020)	(0.114)
Social Capital (Institutional Health)	0.001	0.067	-0.066	0.323
	(0.018)	(0.027)	(0.024)	(0.182)
Population density	259.281	125.924	395.731	0.000
	(30.783)	(8.987)	(61.415)	(0.000)
Age 65 and older in pct	15.887	16.412	15.351	0.054
	(0.075)	(0.115)	(0.093)	(0.025)
		(continues next page)		
	3,140	1,588	1,552	3,140

Table 5: Descriptives and full regression results from Table 1 Column 5, omitting state fixed effects and missing indicators, 2/2

	Descriptives			Regression
		Median Split		
	Mean	High Quality	Low Quality	Tab 1. Col 5
		(continues from previous page)		
Foreign born in pct	4.726	5.112	4.332	0.050
	(0.102)	(0.142)	(0.146)	(0.023)
Ed1 less than high-school in pct	13.402	12.435	14.393	0.082
	(0.113)	(0.162)	(0.154)	(0.026)
Ed2 high-school or diploma only in pct	34.284	33.576	35.007	0.041
	(0.128)	(0.172)	(0.189)	(0.013)
Ed3 some college in pct	21.814	22.751	20.856	0.054
	(0.069)	(0.098)	(0.091)	(0.023)
Ed4 associate degree in pct	8.918	9.110	8.722	-0.024
	(0.048)	(0.066)	(0.068)	(0.024)
Average household size	2.518	2.518	2.518	0.282
	(0.005)	(0.008)	(0.006)	(0.420)
Household 65 plus living alone in pct	12.588	12.745	12.429	0.020
	(0.055)	(0.084)	(0.071)	(0.027)
Premature deaths	8,473.415	8,032.477	8,911.213	0.000
	(48.616)	(67.281)	(68.398)	(0.000)
Population in poor or fair health	0.175	0.164	0.186	3.901
	(0.001)	(0.001)	(0.001)	(5.755)
Population poor physical health days	3.920	3.728	4.117	0.066
	(0.013)	(0.016)	(0.019)	(0.425)
Population poor mental health days	3.931	3.749	4.118	0.293
	(0.011)	(0.014)	(0.016)	(0.425)
Population physical in activity	0.257	0.244	0.270	2.134
	(0.001)	(0.001)	(0.001)	(2.012)
Population life expectancy	77.453	78.063	76.849	0.001
	(0.054)	(0.073)	(0.076)	(0.041)
Air pollution particulate matter	9.022	8.410	9.639	0.011
	(0.035)	(0.054)	(0.039)	(0.044)
Population flu vaccinations	0.405	0.393	0.417	1.670
	(0.002)	(0.003)	(0.002)	(0.615)
Preventable hospital stays	4,826.993	4,362.573	5,295.624	-0.000
	(33.438)	(46.002)	(45.566)	(0.000)
Population adult smoking	0.179	0.168	0.189	-14.808
	(0.001)	(0.001)	(0.001)	(6.215)
Drinking water violations	0.386	0.428	0.341	-0.015
	(0.009)	(0.012)	(0.012)	(0.096)
Population driving alone to work	0.796	0.782	0.810	-1.725
	(0.001)	(0.002)	(0.002)	(1.563)
Residential segregation black white	45.392	49.000	42.830	0.002
	(0.365)	(0.526)	(0.486)	(0.005)
	3,140	1,588	1,552	3,140