The Effect of Hospital Mergers on Quality of Care*

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October 9, 2025

Abstract

We investigate the relationship between hospital mergers and quality of care outcomes across hospitals that serve Medicare. Based on the literature we hypothesize that quality of care outcomes should decrease after a merger occurs. We measure quality as ER wait times and the percentage of ER patients who get a head CT scan within 45 minutes of entering the hospital. We gathered a full panel of data on 3,148 hospitals in the United States over seven years. We use two robust two-way fixed effect models to estimate the difference between merged hospitals and two sets of control hospitals. Our analysis yields weak evidence that ER wait times increase post-merger. Our methods provide inconclusive results relating to head CT %.

Keywords: Hospital mergers, Event study, Quality

JEL Codes: I18, I11, L130, L32

*We would like to thank several people for their much-appreciated help. Dr.Gabriel Lade advised and directed us throughout this project. He also helped identify our empirical approach. We would also like to thank Anthony Ozerov for his sage statistical advice and Jeremy Hubinger for his assistance in overcoming a few key barriers to data cleaning. I, Sahra Jumani, would additionally like to acknowledge, Ahsan Jumani, my uncle who passed away in 2020 for being my biggest motivator in health equity work.

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I Introduction

In 2021, the US spent approximately $4.3 trillion, or about 18.3% of the nation's GDP on healthcare expenditure ("National health expenditure data — cms", n.d.). Just ten years before that, the US spent almost half of that amount, $2.7 trillion on healthcare (Gaynor et al., 2015). The healthcare industry is growing at an exponential rate, and access to healthcare is not only a human necessity, but a healthy economy needs healthy workers. The importance of healthcare is a common understanding, however, whether hospital mergers are beneficial is heavily debated.

The American Hospital Association explains how when hospitals merge, there is a higher quality of care, more services that are available, and exponential innovation (Gaynor et al., 2015). Hospitals hope that by merging there are reduced costs due to shared burden, and more scientific progression due to combined resources, however, whether this is true in practice is uncertain. The effects of mergers and acquisitions on product quality, firm efficiency, market competition, and economic significance have been researched for quite some time, however, the long-term effects of these mergers and acquisitions have yet to be fully understood.

It was until after the 80s that insurance companies and hospitals could negotiate prices, and it wasn't until the 90s that hospitals began merging at a rapid rate (Gaynor et al., 2015). The Herfindahl-Hirschman Index (HHI), a measure of market concentration, was also simultaneously increasing throughout the country as mergers increased. One reason for this influx of mergers was the passing of the Health Maintenance Organization Act of 1973 which removed many of the legal limitations which precluded insurance companies from influencing patient decisions or negotiating rates within hospitals (Gaynor et al., 2015). The HMO Act allowed for less limited negotiation of prices and moved the power from less-price-sensitive patients to highly price-sensitive insurers and hospitals (Dranove et al., 1993). This transition sparked many researchers in the field to question whether hospital mergers are truly effective at cost reduction, or whether mergers actually create inefficiency and higher prices.

Early research regarding mergers was limited to the state of California due to its detailed reporting of healthcare costs, but other mergers such as Evanston-Northwestern and Highland Park-St. Therese & Victory Memoria mergers in Illinois, the New Hanover and Cape Fear merger in North Carolina, and a few others have been studied to observe the effects of acquisitions (Fulton, 2017). Much of the research that has been conducted has solely focused on case-by-case observations of individual mergers, but the findings have not been isolated to specific quality measures. In this paper, we take a more thorough look at how quality changes when there are mergers present.

II Theory

Healthcare Healthcare in this contexts is a variety of highly heterogeneous services provided by a large number of firms in the United States. These services are generally produced with highly skilled labor and large capital investments. Healthcare is provided through a variety of large firms to consumers of healthcare which consist of most people in the United States. Consequently, the healthcare sector is consistently one of the largest in the United States with hospitals and physician services each taking up more than 3.5% of the GDP, and health insurance making up 1% of the GDP (Gaynor et al., 2015).

While there are a variety of competing models to explain interactions within the healthcare industry we can conceptualize the entire industry as working in a series of three distinct stages. First, healthcare providers make investments to create healthcare capacity. They do so with different levels of quantity and in a variety of specific markets. Insurers then observe these markets and negotiate with healthcare providers to create contracts that specify prices and lock providers into specific networks. Insurers, having constructed these networks, then pick premiums to maximize profits. Consumers of healthcare observe insurer networks and prices to determine which plans they want to purchase. Papers in the field have created a wide variety of specific models to examine each one of these stages but few papers examine them as a whole due to model complexity and data limitations (Balan & Brand, 2023). Over the past decades, healthcare has become an increasingly concentrated industry (Gaynor et al., 2012). This conglomeration is still present today as massive insurance and health provider firms continue to dominate the field. This influx has inspired research on healthcare market power and specifically merger events (Gaynor et al., 2015).

Research into healthcare provider consolidation falls into two broad categories. The first has to do with government-regulated markets. The second has to do with publicly operating markets. The key distinction between these is that in regulated markets governments set prices. Firms in these markets only have control over the kinds of services they provide. In public markets, healthcare providers determine both services and prices. Given the public availability of healthcare data in regulated markets and their limited non-price competition, the literature in this area has often focused on the quality of services provided.

Quality Like in any other market healthcare services can be both vertically and horizontally differentiated. Following Gaynor, 2006 the healthcare literature considers these differentiations like any other area of economics. Horizontal differentiation is associated with offering differing healthcare services to appeal to different preferences. Vertical differentiation is when consumers all agree certain services are simply better than others. Vertical differentiation, therefore, is synonymous with product quality.

Product quality can mean a variety of metrics in the industry. Most of these metrics, however, have to do with best practices. Seeing patients more quickly is obviously beneficial to patients. Getting patients the correct care is obviously beneficial to patients and no patient would demand any lower quality product from a provider. Broadly, the literature has often looked at direct measures of patient outcomes like mortality and remissions as metrics of quality. These studies use mortality and remissions metrics as an indicator that some step in the process of care is of a higher or lower quality. More recent literature has posited that using mortality as a determiner of quality can lead to misleading results while looking at specific quality measures gives us an opportunity to observe more specific differences in patient experience (Beaulieu et al., 2020). The literature is varied and mixed on this subject and provides a wide variety of measures of quality. It is fair to say, however, that the quality of healthcare is a multidimensional metric and can not be captured by one measure.

Medicare and Medicaid Medicare and Medicaid are two programs that were initially constructed as amendments to the Social Security Act and passed in the mid-60s to provide care to the elderly and poor, respectively. These programs currently are funded through the ACA or the Affordable Care Act which distributes Disproportionate Share Hospital Payments (DSH) as additional supplemental payments to hospitals and providers that provide Medicaid services. DSH payments are payments made by the United States government to hospitals that serve a specific number of low-income, uninsured, and underinsured patients. These payments are intended to offset the financial burden that these hospitals bear in providing care to a population that is often unable to pay for the services they receive. The amount of DSH payments that a hospital receives is based on a formula that takes into account the hospital's Medicaid and uninsured patient load, as well as other factors. The payments can be used to cover the costs of providing uncompensated care, as well as to support other hospital activities. Historically, reports done by KFF have found that Medicaid payments have been below cost, however, when you account for the additional DSH payments, it seems that Medicaid payments are in excess of cost. A study done by the AHA found that in 202, Medicare reimbursement was 84 cents per dollar and Medicaid reimbursement was 88 cents per dollar ("Fact sheet", n.d.). Contrastingly, when accounting for DSH payments, cost coverage for hospitals ranged from 81% to 107%, depending on the state. The primary distinction between Medicaid and Medicare is that payment rates are negotiated on a state-by-state basis in Medicaid programs while Medicare payment rates are determined on a national level. In addition to the lack of clear data regardings what the costs to hospitals are, the fluctuating nature of DSH payments makes it difficult to predict the effects of competition on hospital mergers. The amount of DSH funding that a hospital receives also depends on the funding formula, which takes into account factors such as the hospital's Medicaid patient volume, the percentage of uninsured patients, and the hospital's overall Medicare utilization rate. The formula is designed to distribute DSH funds to hospitals that have a disproportionate share of low-income patients and uncompensated care costs, but the specific calculation can vary depending on federal and state policies. In some cases, Medicaid hospitals may receive less DSH funding than non-Medicaid hospitals due to factors such as changes in the funding formula or state-level policies that affect DSH allocations (Cunningham et al., 2016).

Competing with Quality Our goal is to examine how the quality of care is affected by market power. To do this empirically we have to isolate quality as our outcome variable and understand what factors might determine the quality of healthcare. It is difficult to estimate exactly what quality healthcare is (Gaynor et al., 2015). We will be focusing on two metrics of the quality of care provided to patience in need of emergency care.

To theoretically link market power and quality we rely heavily on the work of Martin Gaynor et al., 2015 in their paper The Industrial Organization of Health-Care Markets (2015). As previously outlined medicare markets do not have dynamic pricing. Regulators in the Medicare market set fixed prices at a state level, with each state having different qualifying measures for coverage. This means hospitals can only differentiate their product to consumers via quality, similar to other regulated price market models. General fixed price models assume that product quality only increases as long as regulated prices are set above marginal costs of quality. This assumption is based on two prerequisites. First, we assume that it costs more to provide higher-quality healthcare. Second, we assume a Bertrand model of competition where quality instead of prices is the metric competed on. If two comparable hospitals set quality (i.e. marginal cost) to the regulated price they will both split the market share of patients. If one lowers its quality they will lose much or all of their market share. Our theory therefore suggests that competition should have a positive effect on quality of care as without competition there would be less or no pressure to increase quality to the fixed price.

For these assumptions to hold we have to further suppose that fixed prices are above the quality of care any hospital could provide to a patient. Hospitals could, for example, be making profits entirely from non-medicare or Medicaid patients and be trying to not avoid attracting them. Unfortunately, the actual cost of providing various healthcare services is not a publicly available metric at most hospitals. We also did not find direct evidence of this in the literature. Turning to other sources the American Hospital Association (AHA) stated in 2023 that there is a payment gap in Medicare and Medicaid services. They state that reimbursement is below costs. The AHA is not a neutral advocate in this area. The Kaiser Family Foundation (as previously referenced), a non-partisan health policy organization, released a statement in 2016 that agreed hospitals usually lost money on payments from the reimbursement schedule. They do, however, note that Medicaid Disproportionate Share Hospital (DSH) Payments will often put hospitals at a profit for serving these publicly insured patients. The DSH payments are contingent on serving a certain number, not a proportion, of Medicaid patients in a hospital area. This does provide some evidence that hospitals should have an incentive to compete to attract Medicare patients. Following this though since Medicare patients basically face no out-of-pocket differences in costs between hospitals the only metric that a hospital can compete on when attracting these patients is the quality of care they provide.

Given these assumptions, we still assume firms seek profit-maximizing outcomes. If we assume firms are profit-maximizing and only compete via quality to attract consumers we can construct a profit-maximizing equation. Following this model, we can come to build a more general economic model of firm behavior. Following Gaynor et. al (2015) we can construct an estimable model of demand that informs our approach.

(1) $z_j = Z(\overline{p}, W, X_D, N, \epsilon)$

With $\overline{p}$ being fixed prices, W being cost shifters, X_D being demand shifters, N being the number of firms, and ϵ being some error term. These terms create our output a vector of quality z_j which is the quality for each firm $_j$.

Each of these estimators does have some real-world data context that might approximate each effect. P-bar effects are set at a state level over time. Accounting for temporal and state effects, therefore, should address the issues of changing fixed prices. Our key cost shifters are most obviously quality of care costs but also include costs like investments. Demand shifters have to do with the wider age and health demographics of the hospital area. It also should depend on wider macroeconomic events that might shift people in and out of Medicare and Medicaid programs. The number of firms is dependent on the willingness of patience to travel and the population immediately closest to this hospital in the case of emergencies. Finally, quality outcomes are measured by a variety of statistics. These data contexts exist but are unattainable without a lot of resources. This means to approach this topic we will have to turn to a set of hospital comparisons to try and account for all of these effects rather than identify them ourselves.

III Data

To explore whether hospitals that merged or were acquired had lower or higher quality, we utilize three data sets provided by the Center for Medicaid and Medicare Services (CMS). These data sets contain information on hospitals, quality metrics, and acquisitions. All information drawn from the federal agency is publicly available. It is collected for various aspects of provider enrolment and CMS's continuing work to monitor the quality of care provided to enrollees. After completing a data cleaning process —that will be described in more detail— we were left with 3,148 hospitals across the United States for all 7 years we investigated (2016 to 2023).

Hospital Information Our first data set is the *Provider of Services File - Hospital & Non-Hospital Facilities*, or POS files. These files include various basic information about the purpose of hospitals and their various general aspects. It includes information on bed counts, type of hospital, medical school affiliation, and much more. This file provided many of our control and other fixed variables.

Table 1 and Table 2 summarize the hospital statistics for all states and states where mergers occurred, respectively. For the outcome of ER Wait Time, we observe that the mean number of beds in the control and treatment groups are relatively the same on a national level, with non-merged hospitals having about 23 more beds on average. Additionally, though there are slight differences in the percentage of hospitals that have a medical school affiliation or those that are in an urban setting, the treatment and control groups are relatively similar.

Quality Variables The second dataset we used is the *Timely and Effective Care - Hospital* data. The timely and effective care data set over the past 7 years have traced 21 different measures. In the CMS's own words these "...measures of timely and effective care, also known as process of care measures, show how often or how quickly hospitals provide care that research shows gets the best results for patients with certain conditions, and how hospitals use outpatient medical imaging tests (like CT Scans and MRIs)." (CITE) The data is supplied by providers and verified by the CMS. the metrics do not exclusively come from CMS patience. Of the 21 measures tracked 4 are reported for any hospital in all 7 years. Of those four only two are reported for more than 70 hospitals. For this reason, our paper specifically focuses on the variables OP_18b which is the *Average (median) time patients spent in the emergency department before leaving from the visit*, and OP_23 which is the *Percentage of patients who came to the emergency department with stroke symptoms who received brain scan results within 45 minutes of arrival*. The first variable is measured in minutes while the effectiveness of the head CT scans is reported as a percentage from 0 to 100. These variables are important indicators of the effectiveness of care being provided to those who visit hospital emergency rooms and those who suffer from stroke symptoms.

The CMS cites wait times as a primary concern when looking at if emergency rooms are overcrowded or understaffed. In either case, longer wait times can be dangerous for patients and indicate a problem with the care being provided. The CMS also states that any victim suffering stroke symptoms imminently need a brain scan to determine what the appropriate care is and avoid permanent brain damage. Standards of care, according to the CMS, dictate that patients suffering stroke symptoms get a scan within 45 minutes. This measure, therefore, is an obvious quality metric that directly observes if hospitals are taking appropriate measures in dealing with stroke patients. Longer wait times that would lower the percentage of those getting scans within 45 minutes again can suggest overcrowding or understaffing. While ideally a broader range of metrics would be better these do provide a good observation of the level of care being provided to those experiencing emergencies and the resources hospitals put into providing swift and effective care to patients. Even in less extreme cases longer, ER waits are an issue that any patient wants to avoid and can help determine where they might go for care.

Other papers have commonly focused on readmission rates or mortality rates, however, due to data availability we were limited to observing these two variables since they had the only consistently reported data for all hospitals (Sivey & Chen, 2019; Tafti & Hoe, 2022). We did investigate using these metrics. We found, however, that they have not been consistently reported in the Complications & Deaths - Hospitals data (notably there are no reported statistics that include data from 2020). With these limitations in mind, we do believe the timely and effective measures accurately reflect changes in important quality metrics due to an acquisition.

When we cleaned the data for hospitals that contained OP_18b or OP_23 in all 7 years we were left with two distinct data sets. The first contains the aforementioned 3148 hospitals we gathered the POS data for. A subset of these hospitals, 504 of them, have OP_23 data for all 7 years. These two complete panels have the following distribution of outcome variables.

Figure 1 and Figure 2 summarize the ER wait time and CT scan timely and effectiveness over time. The ER wait time is approximately 130 minutes on average and increases slightly in 2021 and 2022. The percent of head CTs completed in 45 minutes averages around 76% and stays relatively consistent throughout the years.

Ownership The final dataset we used is the *Hospital Change of Ownership* (CHOW) data which provides information on changes to hospital ownership for Medicare-providing hospitals. These data are provided as part of the Medicare enrolment process and are updated based on regulations for the purpose of providing public data and information to Medicare recipients. PECOS data is selectively made publicly available. CMS excludes data from public releases that were entered incompletely or incorrectly (CITE). The data contains some 492 observations of changes in hospital ownership between 2016 and 2023.

One significant data issue we face here is how changes of ownership are defined by the CMS. The dataset includes three types of changes of ownership; change of ownership, acquisition/merger, and consolidation. The data contains no consolidations and the CMS elaborates that these are rare. As defined in the CHOW dataset, an acquisition or merger occurs when an enrolled Medicare provider purchases another enrolled provider. A change in ownership is when a Medicare provider has been purchased or leased by another organization. The difference between an acquisition/merger versus a CHOW in this dataset is the status of the provider identification number and not a reflection of the true integration of the hospitals. It is that in the case of a reported change of ownership, the Medicare Identification Number (MIN) is transferred from the previous owner to the new owner while in a merger the previous MIN is dissolved. The old owner or lessee's agreement is typically terminated, while the Medicare Identification Number is transferred from the old owner to the new owner. Though the CMS reports a change of ownership differently than acquisitions and mergers, in economic terms they are both changes of ownership. Identifying if either is a merger of two hospital systems is more complex and not contained in the data.

What the CMS designates as acquisitions and mergers are, in all cases, two hospital systems becoming one; ipso facto the number is dissolved. In the cases of CHOWs some entity is acquiring a hospital but we do not immediately know if that means that the acquirer has ownership of other hospitals. The CHOW data is rife with hospitals being purchased by what appear to be holding companies that are not obviously a separate health system. The CMS does provide a list of owners of the companies acquiring hospitals but in this data two there are sometimes more holding companies that own the hospitals. Turning to the overall ownership records of hospitals released by the CMS in February 2022 we have identified that certain facilities are actually traded between up to 7 holding companies on the day of acquisition. Since transactions between holding companies owned by the same overarching entity are reported by the day and all of these holding company trade-offs occur on the same day the data actually do not contain information on which holding company or which overarching owner some hospitals were acquired by. This obfuscation of ownership may be unintended but it makes it impossible to say with certainty that the CHOWs in the data are being bought by owners who have stakes in other hospital facilities. The doing business names of acquiring companies are, however, listed in the buyer's file. These contain names of companies that appear to all be healthcare providers or facilities and are, in all cases, enrolled in the CMS in the same state as the acquired facility. To the best of our knowledge, therefore, all CHOW purchasers are owners, in part, of other healthcare providers. A deeper investigation of this convoluted data might help address this assumption in the future.

Limiting our events to CHOWs we then further cleaned the data to reach our final data set. Given our event study framework, we need data before and after the acquisitions to ensure we can measure the effect. We limit the data to only CHOWs that occurred after 2019 and before 2021. All hospitals that experienced a CHOW not in this time or acquisition/merger at all were excluded from the data along with any hospitals in the zip codes of any hospital that fell into either of these categories. This excluded hospitals that might otherwise be affected by mergers. In Figure 3 you can see the range of acquisitions this left us with. The chart shows the CHOWs occur throughout the year but some peaks cluster in early 2019. In the larger OP_18b data set this left 94 acquired hospitals; In the OP_23 data set it left 17. That leaves us with 2.9% and 3.3% of hospitals experience acquisitions in our data respectively.

No clear pattern is visible here in the data. A large number of CHOWs clearly take place in 2019 but otherwise, the distribution seems random with some peeks occurring at the beginning of the year. Given this distribution, we felt it was not necessary to dig into said distribution through further research.

The data was all joined and arranged into a panel with variables designating which group each hospital fell into and when hospitals were under the effect of an acquisition. From there on final alteration was made to the data. The data was split into two distinct control groups for estimation. The first contains all hospital data across the United States. The second contains only data from hospitals in states where a hospital was treated. This second data set limits our controls to hospitals with the most similar reimbursement levels to the treatment hospitals. This should give us a more accurate comparison but increases the chance that some spillover effects occur throughout the state when hospitals merge. From there we turned to our empirical methods to analyze and interpret the data.

IV Empirical Methods

We use an event-study framework to compare these merger effects to our control hospitals. Given that our merger effects are temporarily distributed we turn to two-way fixed effect (TWFE) literature to inform our approach. Recent developments in this literature suggest that there are a variety of drawbacks associated with using a simple TWFE model in a setting with more than two time periods.

One key issue in our setting is that the TWFE model does not account for heterogeneity in the treatment outcome. It estimates the average treatment effect. The second issue is that the model does not account for more than two time periods. It might take into account treated hospitals as controls when evaluating newly treated hospitals.

Two accounts for both of these issues we take two approaches to implement robust TWFE models. The first is a stacked difference-in-difference (DID) model developed by Cengiz et al., 2019. This model involves stacking the data with a set of controls and one treatment variable in relative time around the event to manually create two time periods. This approach addresses temporally distributed mergers and weights the estimate with the sample size of the treatment. This method does not address our assumption that control hospitals outside the zip code of merged hospitals are unaffected by the mergers but it deals with the class TWFE model issues in this setting.

Our second approach comes from Callaway and Sant'Anna, 2021 as implemented in their r package *did*. In their approach rather than restructuring the data temporarily they group the treatment variables by the time that a treatment takes place. They then estimate a 2x2 TWFE model for each group-time effect to get a separate average at each time against never-treated controls. This is quite similar to Cengiz but does not require temporal restructuring. It consequently preserves estimates non-relative-time temporal estimates. Methodologically it still labels time relative to the first treatment effect but preserves linear time without any stacking. Callaway & Sant'Anna also implement an aggregation method for their group-time average treatment effects and this is what we use to find our outcome variable estimates. One last area of robustness they add to their method is parallel trend testing conditional on covariates. This robust parallel trends test produces a p-statistic adjusted for observed pre-treatment covariates modifying the traditional assumptions. Their model avoids all classical assumptions made under the DiD and TWFE model but does not address our assumption that control hospitals do not experience spillover effects.

V Results

Cengiz We begin by assessing a parallel trends test for both our broader and more specific control groups. In Table 3 we notice no violations of the parallel trends test. Treatment groups for the relative years before the mergers occur are not experiencing statistically significant trends in either period 1 or 2 that would distinguish them from the controls.

Across both models, we see that relative time effects by themselves have strong significance if not a huge effect. Referring back to the outcome variable data we know that the magnitude of most wait times is in the order of hundreds of minutes. Small 13 minute changes are relatively small effects. Of course, over 94 hospitals and hundreds of patience, all that time can add up and might make a difference in marginal cases. In the case of Head CT scans the median hospital was already quite close to a 75% score. Nonetheless, 12% changes in the Head CT (%) variable are probably relatively impactful. A small improvement in following stroke best practices is important.

In Table 4 we see that parallel trends hold for the two periods before the mergers take place (-2 and -1) in our Head CT (%) variable. The trends test is violated in period -1 for the ER wait time variable as the treatment group is experiencing a relatively significantly distinct trend from the control group (although a p-test of 0.1 is not widely accepted as significant).

That is not the case for the earliest period and this could be an indication that treatment hospitals can anticipate a merger occurring; certainly something to investigate further in the future. There are strong relative time trends once again and broadly these are not incredibly distinct results for halving the observations.

Turning to our actual regression we can see in Table 5 that our interaction variable between treatment and post-merger Acquired is not significant for any model. If we were to discount this significance and look at the variables they do broadly agree with our hypothesis and what the literature might suggest. Mergers, on average, seem to have positive effects on wait times and negative effects on following proper stroke protocols. Without statistical significance, we can not say this to any degree of certainty.

We can also see that our model's key explanatory variables, relative time, bed count, and Acquired, have a very low R^2. Our within R^2 statistic suggests that most of the value of the model is determined by fixed effects. This makes sense since the relative magnitudes of our variables of interest are quite small.

Limiting our control variables to states where treatments took place yields fairly different results accounting for fixed effects. Taking a look at Table 6 we now see a statistically significant merger effect for ER Wait times with about twice the magnitude of our last estimate. The model fairly consistently estimates a $33\dot{5}$ minute increase in ER wait times post-merger. These increased wait times are in line with predictions of inefficiency after mergers. We do also see significant positive effects in the second year after mergers occur in ER wait times. This indicates an overall positive trend in wait times within these states. We also see the magnitude of the bed count estimator stayed exactly the same while becoming less statistically significant. This could be due to a decrease in the variance of the data. The Head CT (%) scores for this second estimation are positive but quite insignificant, as are all the other variables. These estimations are fairly interesting and distinct but suffer some limitations.

All of these estimations should be taken with caution. This ER Wait Time model is the model that just violates our parallel trends assumptions. It did so by a fairly significant margin when compared to the magnitude of these coefficients. The unique and startling significance of the period 2 estimation also is quite interesting relative to the other year's low estimations and is another reason for caution. An increase in significance after a decrease in observations is an interesting phenomenon and one that might support our reasons for limiting the data but it should be viewed in a wider context; luckily we have another set of tests to interrogate all of these previous findings.

Callaway & Sant'Anna The *did* results paint a different and less compelling story than the stacked estimators. Table 7 begins by listing an acrosstheboard violation of the parallel trends assumption when accounting for covariants. All the tests suggest treatment hospitals were experiencing statistically significant unique trends compared to our control variables in the years leading up to merging. This is a much more convincing dispute of the pre-trend assumption than our stacked model provided. When we move into our estimates we also see that in no case are the values statistically significant. We can not infer from these models that post-merger there is any change in ER wait times or CT head scan practices.

Disaggregating this model's estimates to relative times we can see the variety of estimations in Figure 4. For ER wait times there is almost a sine function kind of wave occurring in treatment hospitals. We can see that the margins of error in most cases cross the 0 line. For The first year after mergers in both models, however, we do see a statistically significant rise in ER wait times. Given the slow fall of the estimates afterward, this is an interesting prediction that mergers have a short-term effect on ER wait time outcomes. We do clearly see here, however, that there is a statistically significant trend in wait times before treatment in period -2 across both models. Even accounting for hospital and year-fixed effects it is clear here why these models failed the parallel trends test.

The bottom half of Figure 4 paints a much less clear picture. No estimate on either chart fails to cross the 0. In no period can we confidently estimate any trend in head CT compliance before or after a merger. This is interesting since it would suggest we do not have evidence of a parallel trend but given the small numbers problem of this data set it might just be a consequence of the adjusted methods implemented by Callaway & Sant'Anna. There are no period-specific conclusions that can be drawn from this model which refutes our findings in the stacked DID section.

Our models suggest that with the control variables and data we have there are few consistent or significant predictions of hospital outcomes. The models can not satisfy the parallel trends assumption to estimate a change after mergers occur. The Cengiz model does make several consistent and significant predictions that mergers increase ER wait times but these are disputed by our other model. The one exception to this contradiction is that, disaggregated, our second model does predict that ER wait times should increase the period 1 but this effect decreases over time. This might suggest that there are short-term effects of hospital mergers on ER wait time outcomes but without certainty over parallel trends or consistent predictions, this is a hard case to make. For the Head CT (%) measure no model has significant predictions and our second approach suggests that the model fails a parallel trends test when accounting for covariants. Our predictions were fairly consistent across control groups but inconsistent and insignificant as a whole.

VI Conclusion

Our paper aims to isolate the effects of mergers on specific hospital care metrics such as timely and effective head CT scans and ER wait times. By analyzing Medicare data available through the CMS we utilize an event-study framework to compare the effects of mergers on hospitals that merged versus hospitals that didn't. Additionally, we apply two robust two-way fixed effects models to better identify the effects of mergers on the quality of care. Though we are not able to establish parallel trends, we do find some results to be significant when looking only at states that merged. There are many underlying trends in healthcare outcomes such as longer wait times overall, which make it difficult to extract the effects of mergers on quality of care. Additionally, the lack of data and sufficient research regarding integration post-merger make it difficult to evaluate the degree to which a murder instilled change in administrative or bureaucratic terms. It is also unclear what mechanisms in hospitals contribute to a change in the quality of care outcomes. We are in no way accusing hospitals of making conscious decisions to lower their quality of care. Some profit-slacking mechanisms might be at play. Our limited evidence of an immediate post-merger change in care outcomes might have some impact on this consideration. Overall, more research is needed to better understand the impact of hospital mergers on various aspects of the healthcare system, including quality, cost, access, and workforce. This can help inform policy decisions and ultimately improve the delivery of healthcare services.

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Tables

Table 1: Hospital Summary Statistics for All States

	Wait Time Control	Wait Time Treatment	CT Scan Control	CT Scan Treatment
Mean # of Beds	225.2	202.0	244.1	284.2
Teaching Hos (%)	33.1	23.0	28.2	31.1
For Profit (%)	63.8	52.3	73.7	66.4
Urban (%)	66.5	63.6	74.6	82.4
N	3,054	94	504	17

Table 2: Hospital Summary Statistics for States Where Mergers Occurred

	Wait Time Control	Wait Time Treatment	CT Scan Control	CT Scan Treatment
Mean # of Beds	239.0	206.7	246.0	262.6
Teaching Hos (%)	29.8	22.5	23.3	29.0
For Profit (%)	55.6	50.9	69.0	67.0
Urban (%)	70.1	62.8	71.0	80.0
N	2,255	94	375	17

Table 3: Cengiz Parallel Trends All States

Dependent Variables:	ER Wait Time (Min)	Head CT (%)
Model:	(1)	(2)
Variables		
Constant	148.5***	77.06***
	(3.062)	(0.8174)
Treatment	-8.619*	2.459
	(4.544)	(2.826)
-2	-2.413***	-1.692***
	(0.5547)	(0.5766)
-1	-1.516***	-0.5791
	(0.2832)	(0.3602)
1	4.547***	-0.6135**
	(0.3286)	(0.2644)
2	11.17***	-1.121**
	(0.6802)	(0.5100)
Treatment × -2	0.5482	1.894
	(1.373)	(3.236)
Treatment × -1	-0.4616	0.6261
	(0.8750)	(1.465)
Treatment × 1	1.156	-1.947
	(1.039)	(1.744)
Treatment × 2	2.388	-0.1696
	(2.106)	(1.501)
Fit statistics		
Observations	47,233	7,560
R^2	0.01558	0.00305
Adjusted R^2	0.01517	0.00045

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 4: Cengiz Parallel Trends Treatment States

Dependent Variables:	ER Wait Time (Min)	Head CT (%)
Model:	(1)	(2)
Variables		
Constant	147.5***	78.59***
	(3.608)	(0.7930)
Treatment	-6.958**	2.088
	(3.252)	(2.574)
-2	-1.284*	-1.605***
	(0.6752)	(0.5477)
-1	-0.9954**	-0.6912
	(0.3770)	(0.4584)
1	5.272***	-0.9370**
	(0.6616)	(0.4097)
2	12.09***	-2.075***
	(1.142)	(0.5108)
Treatment × -2	-0.5930	1.155
	(1.695)	(2.216)
Treatment × -1	-1.975*	-0.7838
	(1.082)	(1.259)
Treatment × 1	1.408	-0.0380
	(1.374)	(1.587)
Treatment × 2	2.859	0.6753
	(2.467)	(1.616)
Fit statistics		
Observations	21,623	3,455
R^2	0.01558	0.00305
Adjusted R^2	0.01517	0.00045

Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5: Cengiz DiD All States

Dependent Variables:	ER Wait Time (Min)			Head CT (%)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Acquired	1.819	1.742	1.760	-1.845	-1.815	-1.838
	(1.807)	(1.802)	(1.822)	(2.428)	(2.435)	(2.466)
Bed Count		-0.0153*	-0.0153*		0.0094	0.0094
		(0.0088)	(0.0088)		(0.0153)	(0.0153)
-2			-0.0004			-2.97×10^{-5}
			(0.0008)			(0.0014)
-1			-0.0009			-0.0013
			(0.0008)			(0.0019)
1			-0.0519			0.0656
			(0.0567)			(0.0882)
2			-0.0533			0.0670
			(0.0569)			(0.0887)
Fit statistics						
Observations	47,233	47,233	47,233	7,560	7,560	7,560
R^2	0.88863	0.88868	0.88868	0.60472	0.60485	0.60489
Within R^2	0.00011	0.00055	0.00057	0.00025	0.00058	0.00069

Fixed-effects Controlled for: Year, Hospital Level, Ownership Type, Medical School Affiliation, and Urban/Rural
Clustered (State) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 6: Cengiz DiD Treatment States

Dependent Variables:	ER Wait Time (Min)			Head CT (%)		
Model:	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
Acquired	3.519**	3.414**	3.033*	0.4864	0.6112	0.6871
	(1.676)	(1.662)	(1.719)	(1.865)	(1.864)	(1.883)
Bed Count		-0.0154	-0.0152		0.0297	0.0297
		(0.0102)	(0.0101)		(0.0209)	(0.0209)
-2			-0.6755			0.3851
			(0.5895)			(0.5263)
-1			-0.4744			-0.1492
			(0.3228)			(0.3214)
1			0.6364			-0.2568
			(0.4155)			(0.3497)
2			2.365***			-0.3784
			(0.6949)			(0.6051)
Fit statistics						
Observations	21,623	21,623	21,623	3,455	3,455	3,455
R^2	0.88942	0.88948	0.88965	0.63937	0.64091	0.64100
Within R^2	0.00065	0.00123	0.00274	3.32×10^{-5}	0.00430	0.00455

Fixed-effects Controlled for: Year, Hospital Level, Ownership Type, Medical School Affiliation, and Urban/Rural

Clustered (STATE_CD.x) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 7: Callaway & Sant'Anna DiD

Data	Treatment States		All States	
Variable	Wait Time	CT %	Wait Time	CT %
Pre-Trends P-Test	0.023	0.000	0.035	0.002
Acquired	4.100	1.115	3.462	1.406
Standard Error	1.869	2.665	1.865	2.377
95% Conf Low	-1.794	-2.558	-1.790	-2.282
95% Conf High	5.533	7.887	5.520	7.037

Controlled for: Year, Hospital Level, Ownership Type, Medical School Affiliation, and Urban/Rural

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Figures

Figure 1: ER Wait Summary

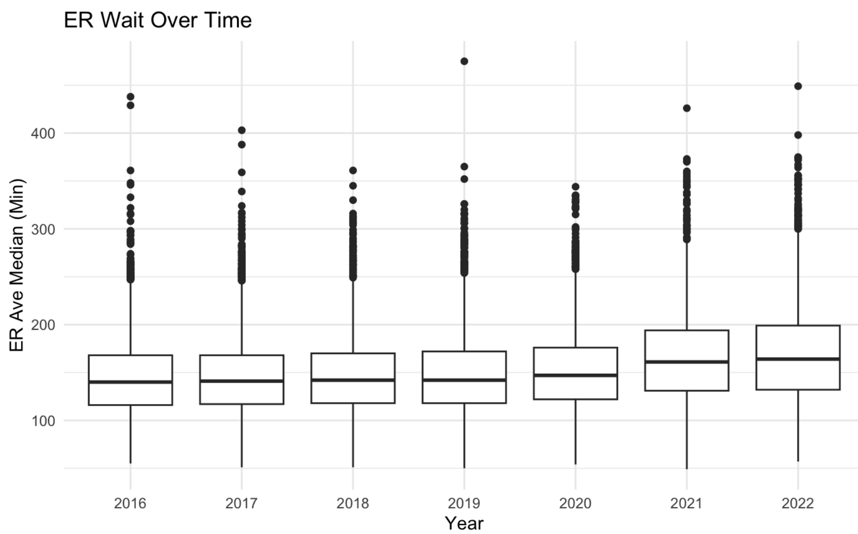

Figure 2: CT % Summary

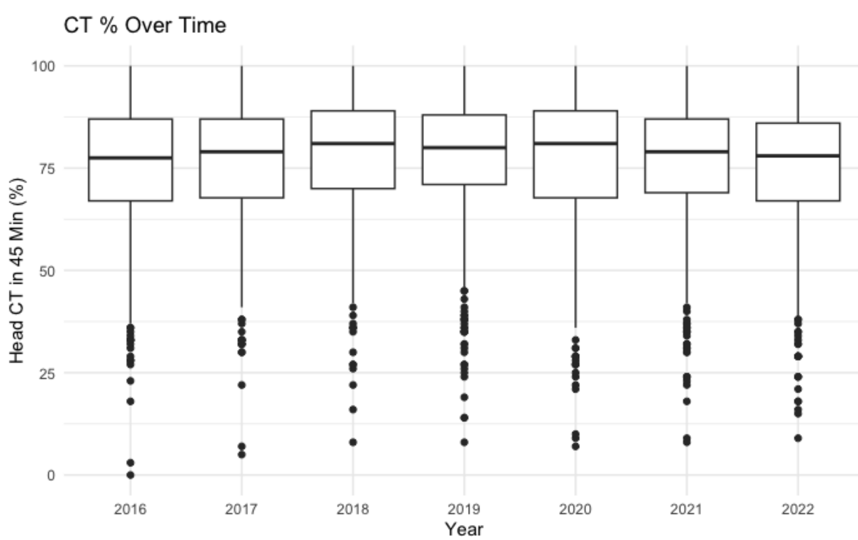

Figure 3: Temporal Distribution of CHOWS

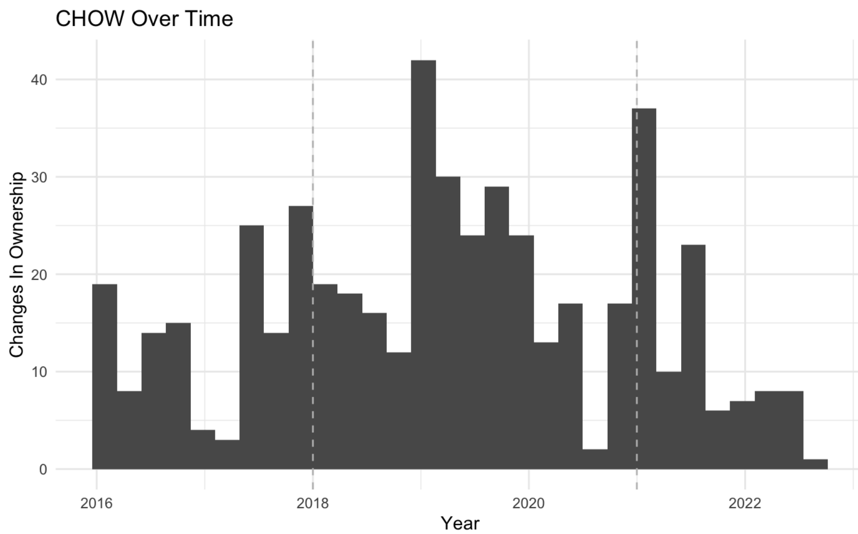

Figure 4: All Effect by relative exposure Callaway & Sant'Anna DiD graphs