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Pinka Chatterji
Chun-Yu Ho
Wenqing Li

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ABSTRACT

This paper examines the impact of mergers between nursing home chains and independent facilities on quality of care, utilizing facility-level data from 1999–2019. Using a staggered difference-in-differences framework, we find that acquired facilities experience an 8% reduction in health deficiency citations in the three-year period post-merger. This effect persists for at least five years and is more pronounced in cross-market mergers, as well as mergers involving smaller or low-deficiency chains. Estimating a structural model suggests that this decline in deficiencies is driven by post-merger reductions in the marginal costs of serving residents. However, this cost efficiency is accompanied by a decline in direct care hours. Furthermore, the reduction in deficiencies is concentrated on low-severity categories, suggesting that mergers improve regulatory compliance rather than clinical outcomes. Consistently, we find no meaningful impact of mergers on residents' health outcomes.

Pinka Chatterji
State University of New York at Albany
Department of Economics
and NBER
pchatterji@albany.edu

Wenqing Li
State University of New York at Albany
Department of Economics
wenqing.li@hotmail.com

Chun-Yu Ho
State University of New York at Albany
Department of Economics
cho@albany.edu

A data appendix is available at http://www.nber.org/data-appendix/w33967

1 Introduction

Horizontal merger is a strategy that is frequently adopted by firms to achieve a competitive advantage over their rivals. Models of horizontal mergers, however, typically postulate that there is a trade-off between efficiency gained through the consolidation of units and reduced competition (Williamson, 1968; Farrell and Shapiro, 1990). It is therefore imperative to understand how mergers affect unit-level efficiencies as well as the effects of reduced competition on prices and quality. This is especially relevant today given the growing concentration in various industries, including the healthcare, manufacturing, retail, technology and transportation sectors.[1]

The Federal Trade Commission (FTC) has been conducting retrospective analyses of mergers since the 1980s. Not all mergers, however, trigger antitrust scrutiny. An exception of growing importance is the acquisition of an independent healthcare facility by a chain in cases where the acquirer and the target do not compete in the same geographical market (Eliason et al., 2020; Andreyeva et al., 2024; La Forgia and Bodner, 2025). We know little about the effects of these kinds of mergers on outcomes. In addition, much less of the effects of mergers are known when quality serves as a key dimension of competition, which is more prevalent in the healthcare industry. In this paper, we explore the effects of mergers in the healthcare sector on quality of care by examining a series of mergers between nursing home chains and independent nursing facilities.

There are several advantages of examining the nursing home industry for our objective. First, the poor quality of some nursing homes in the US has been a long-standing problem for decades. Examples of quality issues include high-stage pressure ulcers among long-stay residents, high rates of preventable hospitalization of residents, and potentially inappropriate medication use (Harrington et al., 2017). The effects of nursing home mergers on quality of care deserve a thorough investigation as nursing homes host more than 1 million residents and receive more than $100 billion from payers each year.[2]

Second, the supply of nursing homes has declined appreciably over the past decade (Hughes et al., 2023; Miller et al., 2023). More than half of U.S. counties lost a nursing home facility between 2000 and 2019.[3] Further, multi-facility chains have emerged as important players in the nursing home industry over the last two decades, owning about 55% [4] of nursing homes. In particular, there were about 3,741 independent nursing homes merging with multi-facility chains between 2000 and 2019.[4] These market dynamics provide a unique setting to identify the quality effects of mergers.

Third, around 76% [4] of nursing home residents are covered by either Medicare or Medicaid and the reimbursement rates for these residents' stays are determined by federal or state government

[1] See *Benefits of competition and indicators of market power* by Council of Economic Advisors in 2016

[2] See https://www.kff.org/medicaid/issue-brief/a-look-at-nursing-facility-characteristics-through-july-2022/ and https://www.genworth.com/aging-and-you/finances/cost-of-care/cost-of-care-trends-and-insights.html/

[3] This decreasing supply trend is related to the closure of nursing homes primarily caused by financial challenges (Lord et al., 2020).

[4] These figures are computed by the authors using CASPER data. Also, the count of mergers here is larger than that presented in Table 1 as it represents the count of mergers in the CASPER dataset prior to its merger with the HCRIS dataset and the application of sample selection criteria.

authorities. Since nursing homes have almost no control over the prices they charge for patients supported by Medicare or Medicaid, quality of care, instead of price, becomes a key variable of competition.

This paper examines the quality effects of mergers among skilled nursing facilities (SNFs) in the U.S. from 1999 to 2019. Our empirical analysis is based on two datasets. We obtain facility-level information on nursing home operations, resident characteristics, and regulatory compliance status from the Certification and Survey Provider Enhanced Reporting (CASPER) system. We then merge the CASPER data with facility-level financial information from the Healthcare Cost Report Information System (HCRIS).

The empirical approach takes three steps. First, we conduct a staggered difference-in-differences (DID) analysis to identify the causal effect of mergers on nursing homes' count of health deficiency citations. Here, our main quality measure of interest is the number of health deficiency citations following (Chen and Grabowski, 2015; Grabowski et al., 2016). The treatment group consists of independent nursing homes acquired by multi-facility chains. The control group is constructed from a pool of always-independent facilities using a matching model. Our baseline results imply that, on average, acquired facilities experience a reduction of 0.5 unit in the number of health deficiency citations in the three-year period following the merger. This is an improvement translating to an 8% reduction evaluated at the average number of health deficiency citations among nursing homes. The effect grows stronger over time and persists for at least five years following mergers. These improvements are observed specifically in mergers between chains and independent homes, but not in other types of transactions such as chain-to-chain transactions.

The second step is to understand the potential mechanisms behind the observed fall in deficiencies. To do so, we develop and estimate a structural demand and supply model of nursing home competition. On the demand side, we estimate a standard discrete choice model of nursing home demand. On the supply side, we develop an imperfect competition model in which nursing homes compete along quality. Specifically, we allow mergers to affect the supply of quality in three ways: 1) mergers affect the marginal cost of serving residents; 2) mergers affect the marginal cost of providing quality; and 3) mergers internalize the competition between merged facilities in the same market, which in turn increases market power and reduces quality. Encouragingly, our structural model produces quantitatively similar results as the DID analysis regarding the drop in deficiencies in response to mergers. The structural model further reveals that the driving force underlying the reduction of deficiencies mainly comes from a lower marginal cost of serving residents post-merger. This finding is further supported by evidence indicating a decreased cost of inpatient routine services per resident. Notably, mergers involving small and low-deficiency chains generate greater cost-efficiency gains and larger reductions in deficiency citations, whereas within-market mergers appear to be driven more by market power and achieve smaller reductions in deficiencies.

Thirdly, we examine other quality measures to understand whether the decline in deficiency citations translates into a higher quality of care. We find that there is a shift in staffing composition toward greater reliance on licensed practical nurses. Alongside adjustments in staffing, direct care hours per resident day decline following mergers, so do skilled nurse hours. Further, the reduction in health deficiencies is concentrated in low-severity categories, suggesting that the observed effects on deficiencies may reflect improved compliance rather than genuine increase in quality, especially given the decline in direct-care staffing. Consistently, there is no meaningful improvement among the five health measures we examine. One possible explanation is that independent nursing homes acquired by chains become more adept at responding to inspections, resulting in fewer deficiency citations even if underlying quality remains largely unchanged throughout the years.

The rest of the paper proceeds as follows. Section 2 develops a theoretical framework and presents a literature review. Section 3 describes the data. Sections 4 and 5 present the DID and structural analyses, respectively. Section 6 discusses staffing and health outcomes. Section 7 concludes.

2 Theoretical Framework and Literature Review

This section first discusses a theoretical framework that elaborates on how mergers can affect the quality of care in nursing homes. Then, it reviews the literature and outlines our contributions to the existing body of research.

2.1 Theoretical Framework

Figure 1 illustrates the two channels through which mergers can affect the quality of nursing home care, namely market power and cost efficiency. First, mergers reduce competition when they result in more nursing facilities being operated under the same owner in a market. Since nursing homes have limited control over the prices they charge (as mentioned previously, most residents are covered by Medicaid or Medicare, public payers that set their own rates), they may compromise on quality in response to reduced competition. Another factor potentially contributing to the decline in quality of care after merger is that acquired facilities may converge to the behavior of their new parent companies (Eliason et al., 2020). Nursing home chains are more likely to be for-profits than independent facilities. When mergers occur between for-profit chains and nonprofit independent homes, the latter may adopt the more-profitable strategies and practices to align with those of their for-profit owners, which can lead to a decline in the quality of care.

On the other hand, mergers can enhance cost efficiency in several ways. First, mergers may eliminate redundant and inefficient use of resources. For example, merged nursing homes can generate cost savings by consolidation of duplicate administrative functions and scale economies in the effective use of electronic medical record systems (Schmitt, 2017). Mergers can also improve capacity utilization by mitigating the "peak load problem," allowing more efficient use of fixed resources Lynk (1995). Second, independent nursing homes can benefit from mergers by learning the best practices from the chain. These include improved efficiency in administrative functions through corporate standardization (Kamimura et al., 2007), and intercompany transfer of employees (Dyer et al., 2004) within a chain. Third, a chain-owned nursing home can replace the existing management of an independent nursing home, who might have run the nursing home poorly. Such management turnover reduces agency problems and increases management effort, and hence improves cost efficiency (Walsh, 1988). The reduced agency problem will also help to transfer cost saving to quality improvement by reducing waste due to managerial inefficiency. In sum, if the cost savings realized from mergers are invested in quality enhancement, such as recruiting nursing staff to increase hours of care on patients, then quality of care might improve.

Further, cross-market mergers are dominant in the nursing home industry. They account for 71% of our sample mergers. Cross-market mergers provide the efficiency gain mentioned above and are free from the market power concern that may arise in within-market mergers. Nonetheless, recent literature raises several market power concerns associated with cross-market mergers, one of which is more applicable in our setting. Nursing home chains might compete with each other across markets. A chain-owned nursing home may be reluctant to improve quality in one market, fearing that its competitor will retaliate by increasing quality in other markets.[5]

In summary, the overall effect of mergers on nursing home quality depends on whether the cost-efficiency component or the market-power component dominates (See Figure 1 for a schematic summary). Our structural model in Section 5 is designed to disentangle these two effects.

2.2 Literature Review

This paper contributes to two strands of literature. First, there is a literature investigating the effects of chain ownership on nursing home performance, but findings are mixed. On the one hand, Banaszak-Holl et al. (2018) finds a higher degree of staffing standardization among nursing homes owned by the same chain, which suggests the presence of a common quality control framework that extends across the homes within the chain. Blackburn et al. (2018) finds that chain-owned nursing homes are more likely to adopt Alzheimer's disease special care unit (SCU) beds compared to independent homes. On the other hand, Grabowski et al. (2016) finds that chains tend to target low-quality nursing homes as merger candidates but do not necessarily reduce deficiencies after merger transactions.

We contribute to this literature in several ways. First, our study finds a significant drop in deficiencies following mergers, which is in contrast to Grabowski et al. (2016). We interpret the difference as relating to our approach improving over theirs. Our analysis focuses on a recent period from 1999 to 2019 (vs. an earlier period from 1993 to 2010 in their study) and applies a more credible causal inference method based on a matching and stacked DID approach. Further, we explore the heterogeneous effects of different types of mergers, and the effects of mergers on staffing outcomes as well as resident health outcomes.

Second, there is a literature examining the quality effect of mergers, showing mixed effects.

[5] Another market power concern about cross-market mergers is that a cross-market chain can negotiate better contract terms with the insurer, which can lead to higher prices and a potential reduction in quality. This is less applicable in our setting because not many residents are paid by private insurers for long-term care.

Previous studies in the airline industry show more positive effects of mergers on quality (Prince and Simon, 2017; Chen and Gayle, 2019) compared to the newspaper (Fan, 2013) and pharmaceuticals (Haucap et al., 2019) industries, while previous studies on hospital mergers show mixed effects on quality (Gaynor et al., 2015; Beaulieu et al., 2020). In a closer relationship to our work, Eliason et al. (2020) and Andreyeva et al. (2024) find that chain acquisition of independent dialysis facilities and independent hospitals decreases quality respectively, while La Forgia and Bodner (2025) find that chain acquisition of independent fertility clinics increases quality.

We contribute to this literature by providing a novel retrospective study on nursing home mergers, specifically focusing on their effects on quality of care. In addition, we develop a novel structural model to supplement the standard DID approach commonly used in retrospective studies of mergers. The advantage of using our structural model is that it breaks down the quality effect of mergers into three components, namely cost efficiency in serving residents, cost efficiency in providing quality, and market power. Our model clarifies the potential mechanisms behind the quality effects and can be applied to settings where there is only non-price competition, such as the healthcare industries in Canada and the U.K.

3 Data

This paper employs two main data sources. The first is the CASPER database (previously called Online Survey Certification and Reporting (OSCAR) before 2012) which is maintained by the Centers for Medicare and Medicaid Services (CMS). This database contains facility-level information on nursing home operations, resident characteristics and regulatory compliance status from state surveys of all federally certified Medicare and Medicaid nursing facilities in the US. The surveys are conducted at least once every 15 months for each nursing home.[6] We obtain merger information, quality measures, and facility-level characteristics from the CASPER database. The second is HCRIS, maintained also by the CMS. The database contains annual cost reports submitted by every Medicare-certified skilled nursing facility (SNF) in the US. The cost reports contain information about costs, revenue, and other financial data for each reporting facility.

3.1 Sample Selection

Our sample is constructed at the facility-year level. We select our sample with the following criteria. First, we limit our sample to the 48 U.S. contiguous states for the period 1999 to 2019. Second, the HCRIS data is matched to the CASPER data by a unique nursing home provider number. Because HCRIS only contains information on SNFs, our sample focuses on SNFs instead of all

[6]For nursing homes that had gaps between survey years but multiple surveys in the preceding or following year, we impute the missing data using the survey information closest to the gap year. Approximately 0.3% of observations were removed from the final sample due to unresolved gaps between years. Please note that only discontinuity within the 7-year event window results in exclusion from the analytic sample. Gaps in survey years outside this seven-year event window are permitted.

nursing facilities in general.[7] Third, since our paper focuses on nursing homes for residents with long-term care needs, similar to Ching et al. (2015) and Hackmann (2019), we exclude nursing homes that primarily target Medicare residents requiring short-term rehabilitative care as opposed to long-term care for their chronic disabilities.[8] Fourth, we require that the acquired facilities have at least three years of data prior to and at least three years of data after mergers and control facilities have at least seven years of data in our sample period. Doing so will make our analysis cover mergers that were consummated from 2002 to 2016. Fifth, if the acquired facilities have more than one merger in our sample period, we only look at their first merger.[9]

3.2 Mergers

We take several steps to identify mergers between independent and chain-owned nursing homes. First, we obtain the chain ownership information based on a text field "Name of Multi-Facility Organization" in CASPER. This text field provides information on whether a facility is owned by a chain and the name of the chain if it is. We then create an ownership variable, which indicates whether a nursing home is "independent" or "chain-owned" for each observation year.[10]

Second, if a nursing home reports itself to be "chain-owned" in the current survey but was reported as "independent" in the previous survey, we consider this independent nursing facility to have been acquired by a chain at some point between the two survey dates. Figure 2 depicts that, over the period 2002-2016, there were on average 60 mergers identified between independent nursing homes and nursing home chains in our sample, among which more were consummated in the earlier years. The nursing home chains involved in those mergers have 15 facilities on average (see Table 1 Panel A).

Two complications are involved in identifying mergers with our approach. One complication arises from mergers that result in changes in provider numbers, which disguise as new entries. To address this, we utilize the provider identifiers, developed by the LTCFocus, to track facilities over time despite changes in name or ownership.[11] To capture independent nursing homes acquired by chains but experience changes in provider number, we search for nursing homes changing their provider number but retaining the same street address reported in CASPER [12]. Another complication is the lack of precise merger dates. Because the exact timing of each merger is unavailable, we assume that the deal occurred in the year of the survey in which the previously

[7] Specifically, 17.5% of the observations in the CASPER data cannot be matched to the HCRIS.

[8] Homes whose Medicare shares exceed 90 percent are excluded from our sample following Hackmann (2019). These facilities are not relevant for our demand analysis in section C1 as they compete in a different market.

[9] There are two possibilities here. First, an independent facility is acquired by a chain and then sold and becomes independent. Second, an independent facility is acquired by a chain and then sold to another chain.

[10] We checked chain names carefully to reduce mistakes due to typos and abbreviations in names across years. We also tried to reduce errors by drawing on information from company websites, government reports and media coverage of nursing home transactions.

[11] We utilize the provider identifier crosswalk file downloaded from LTCFocus website, https://ltcfocus.org/. LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health.

[12] Of the 895 mergers included in our sample, 13 involve a change in provider number.

independent nursing home reported itself to be chain-owned for the first time.

In this paper, geographic markets are defined at the county level following previous studies, see Grabowski and Hirth (2003), Lin (2015), and Zhao (2016). Evidence suggests that seniors seldom cross county borders to seek nursing home care services and the majority of nursing home residents choose a nursing home located in the county in which they resided before entering the home (Gertler (1989), Nyman (1985), Bowblis (2012)). Given the geographic market definition, we define two types of nursing home mergers, one being within-market mergers and the other being cross-market mergers. A within-market merger happens when the acquirer has facilities in the same county as the target facility. A cross-market merger happens when the acquirer enters a new market by acquiring a facility outside of its service counties. Table 1 Panel A reports that almost 3 out of 4 nursing home mergers are cross-market mergers.

3.3 Quality

During the annual surveys, the state surveyors evaluate both the operation and outcomes of nursing homes for around 175 individual requirements across eight major areas.[13] Whenever a facility fails to meet a requirement, a deficiency citation is given to the facility for that individual requirement. In 2015, the most common deficiencies were given for failures in infection control, accident environment, food sanitation, quality of care, and pharmacy consultation, see Harrington et al. (2017).

The CASPER database contains details about each citation issued. We choose the count of health deficiency citations ($hdeficiency$) as our main measure of quality. The count of deficiency citations has been used as a quality measure in the literature, for example, Chen and Grabowski (2015) and Grabowski et al. (2016). We focus on health deficiencies as opposed to all deficiencies because these are more related to residents' health outcomes. A higher level of deficiency citations implies lower quality.

3.4 Facility Characteristics

We obtain facility characteristics from CASPER and HCRIS. The following variables are included in the analysis:

- $nonprofit$: an indicator of whether or not the facility is not-for-profit
- $government$: an indicator of whether or not the facility is owned by state/local government authorities
- scu: an indicator of whether or not the facility has any special care unit (SCU)
- $wage$: average hourly wage of the nurses working in the facility

[13] Administration, environment, mistreatment, nutrition, pharmacy, quality of care, resident assessment and resident rights.

- *Medicaid*: percentage of facility residents whose primary payer is Medicaid
- *Medicare*: percentage of facility residents whose primary payer is Medicare
- *totbeds*: total number of beds
- *acuity*: acuity index; a measure of the level of care needed by a nursing home's residents. It is computed based on the number of residents in need of various levels of activities of daily living (ADL) assistance and the number of residents receiving special treatment.[14]

4 Difference-in-Differences Analysis

To evaluate the effects of nursing home mergers, we first conduct a DID analysis. Acquired facilities are referred to as the "treatment group", whereas facilities that remain independent for the entire sample period are referred to as the "control group". Mergers would have effects on quality if the quality trend at the acquired facilities significantly differed from that at the control facilities after mergers.

The selection of the treatment group may not be random but based on facility characteristics. As a result, the difference in quality trends after mergers between the acquired and control facilities can be confounded by their characteristics. We perform 1-to-1 optimal Mahalanobis matching to select a group of independent facilities that are more similar to the acquired facilities on observed dimensions in year $\tau_i - 1$, i.e. one year before mergers, for the DID analysis. See Appendix A for the details of matching.

Table 1 Panel B reports the summary statistics of our sample. On average, facilities receive about 6 health deficiency citations in a year. Treatment facilities receive 0.4 citation more than control facilities; i.e. low-quality nursing homes are more likely to be targeted for mergers, which is consistent with Grabowski et al. (2016). Further, acquired and matched control facilities are similar in other dimensions. Around 27.5% of the nursing homes are not-for-profit and 3.3% of the nursing homes are owned by state/local governments. More than 70% of the residents are supported by Medicaid or Medicare, while the remaining 30% of the residents are supported by private payers. Bed capacity for an average-sized nursing home is around 112. About 22.5% of the nursing homes have at least one special care unit. Nurses are paid on average \$15.6 an hour.

[14]Follwing Cowles (2016), the acuity index is calculated using the following formula: adlindex + stindex + addindex; where adlindex equals (N eating-dependent residents X 3) + (N eating-assisted residents X 2) + (N eating-independent residents) + (N toileting-dependent residents X 5) + (N toileting-assisted residents X 3) + (N toileting-independent residents) + (N transfer-dependent residents X 5) + (N transfer-assisted residents X 3) + (N transfer-independent residents) + (N bedfast residents X 5) + (N chairbound residents X 3) + (N ambulatory residents) divided by (total N residents); stindex equals (N residents receiving respiratory care) + (N residents receiving suctioning) + (N residents receiving IV therapy) + (N residents receiving tracheostomy care) divided by (total N residents); and addindex equals (N residents with dementia) + (N residents with psychiatric diagnosis) + (N residents with retardation) + (N residents receiving PT, OT or speech therapy) + (N residents receiving tube feedings) divided by (total N residents).

4.1 Model

In our setting, facilities are treated in different years. Recent literature challenges the use of the two-way fixed effects (TWFE) approach to estimate DID models with staggered adoption designs (Goodman-Bacon, 2021).[15] We follow Cengiz et al. (2019) to create a stacked dataset that enforces comparisons between treated and never-treated facilities. To be specific, facilities treated in different years are put into different cohorts along with their untreated counterparts selected by matching (see Appendix A for details). For each cohort of facilities, we create a data set to include observations in an event window around the year of merger for the treated facilities, i.e. 3 years pre-merger and 3 years post-merger. We include the observations of control facilities over the same sample years as their treated counterparts. All the cohort data are then pooled together into one data set to estimate the average treatment effect.

The stacked DID model estimates the following equation for facility i in cohort c in year t:

$$Quality_{ict} = \gamma \cdot 1[i \in T, t \geq \tau_i] + X_{ict}\beta + a_{ic} + \lambda_{tc} + {}_{ict} \tag{1}$$

Where 1[] is an indicator function that equals one if facility i is in the treatment group (T) and the year t is after facility i's year of merger (τ_i). We control for the observed and unobserved quality differences across facilities with a vector of facility characteristics X_{ict} and facility-cohort fixed effects (FEs) a_{ic}, respectively. The vector of facility characteristics X_{ict} includes the characteristics discussed in Section 3.4, but we are concerned that few of those variables might be endogenous as mergers can potentially change these variables - for example, patients with high acuity profiles get discharged post merger. In addition, new evidence suggests that nursing homes conduct selective admission practices that disproportionately harm Medicaid-eligible patients with lengthy anticipated stays, see Gandhi (2020). To address these concerns, we include the following county-level variables - number of beds in market per 1,000 individuals aged 65+, mean acuity index, mean share of patients with Medicare, and mean share of patients with Medicaid as control variables instead of the facility-level versions of those variables [16]. We control for the aggregate non-linear quality trend for each cohort over time by including year-cohort FEs λ_{tc} in the model.

Further, we include state-specific time trends in our model to control for potential variations in the trend of deficiency citations at the state level. As suggested by Banaszak-Holl et al. (2002), there may be systematic differences in deficiency citations across states as the citations are issued based on surveys conducted by each state.

[15] The primary concern lies in the "forbidden comparisons" that the TWFE estimator utilizes facilities treated at earlier periods as controls, making it more likely to have negative weight issues and lead to estimators that could barely be interpreted as average treatment effects. Therefore, the TWFE estimator is not robust to heterogeneous treatment effects across facilities and periods.

[16] Using facility-level version of these variables have minimal impact on our results.

4.2 Results

4.2.1 Baseline Results

This subsection reports the results from the stacked DID estimation. Columns (1) and (2) of Table 2 presents our main result with the use of a 3-year event window around the year of mergers. Column (1) reports the estimates without control variables. The findings remain consistent across specifications with and without controls: the number of health deficiency citations is significantly reduced by 0.5 units for the acquired facilities in the three-year period after mergers, relative to the control facilities, representing an 8% reduction below the mean after independent facilities are acquired by chains. The effect is stronger with a longer post-merger period, see section 4.3.3 for details.

4.2.2 Event Study

A key identifying assumption of the DID model is that the acquired facilities share a common trend with the control facilities had they not been acquired by chains. Otherwise, the quality effects of mergers might be due to the fact that the quality trend at the acquired facilities is different from that at the control facilities before mergers take place. Here, we test whether the acquired and control facilities have common trends pre-merger by estimating the following equation.

$$Quality_{ict} = \sum_{k=-3}^{k=3} \gamma_k \cdot 1[i \in T, t = \tau_i + k] + X_{ict}\beta + a_{ic} + \lambda_{tc} + \epsilon_{ict} \tag{2}$$

The coefficients γ_k's, where $-3 \le k \le -2$, are used to test the common trend assumption. If the coefficients are close to zero, this means that the acquired facilities share a similar quality trend with the control facilities in the three-year period prior to mergers. The year before mergers, $t = \tau_i - 1$, is the omitted category (i.e. $\gamma_{-1} = 0$).

The upper left panel of Figure 3 depicts the event study estimation for our main sample. The coefficient estimate of $1[i \in T, t = \tau_i - 3]$ and $1[i \in T, t = \tau_i - 2]$ are close to zero and statistically insignificant (the coefficient estimates are presented in Appendix B Table B1). These results suggest that there is no significant difference between the acquired and control facilities in terms of health deficiencies in the three-year period before mergers. Our event study results support the causal effect of mergers on facilities' health deficiency citations.

Inspecting the coefficient estimates for post-merger indicators (see Figure 3), we notice those of $1[i \in T, t = \tau_i]$ and $1[i \in T, t = \tau_i + 1]$ are either insignificant or only marginally significant, whereas the coefficient estimates of $1[i \in T, t = \tau_i + 2]$ and $1[i \in T, t = \tau_i + 3]$ are negative and significant at 1 % level. This implies that the number of health deficiency citations experiences only a modest reduction in the year of the merger and the year following it. In the second and third year post-merger, the number of health deficiency citations is reduced significantly by 0.842 and 0.887 units respectively, which translates to a 14% and 15% reduction from the average number of health deficiencies among nursing homes. These results suggest that potential quality improvement takes time to materialize, with the number of deficiency citations gradually decreasing over time.

4.3 Robustness

4.3.1 Two Way Fixed Effects

Our main results are based on the stacked DID approach which incorporates facility-cohort fixed effects and year-cohort fixed effects in the regressions. As a second robustness check, we reanalyze the data using the traditional two-way fixed effects (TWFE) approach. Column (3) of Table 2 present the results from the TWFE approach, where facility and year fixed effects are included instead of facility-cohort and year-cohort fixed effects.

Comparing the coefficient estimates between the TWFE and stacked DID approaches, the results from the TWFE approach also indicate a decline in deficiencies following mergers, but the magnitude of the effect is significantly smaller. This is consistent with the Goodman-Bacon (2021) finding that the effect is underestimated if the treatment effect grows over time (the bias mainly comes from comparisons of later to earlier-treated groups because previously treated controls will still be reacting to treatment when used as controls later). In fact, our event study resultreported in Figure 3 suggests that the merger effect does become larger as time goes by, see section 4.2.2 for more details.

4.3.2 Exit

One potential identification concern arises from omitted variable bias driven by nursing homes that exited over the sample period. The supply of nursing homes has declined over the past decade (Hughes et al., 2023; Miller et al., 2023), and our analysis of CASPER data indicates that more than half of U.S. counties lost at least one nursing home facility between 2000 and 2019.

An alternative explanation is that the closure of nursing homes reduces local supply, increasing patient demand at the remaining facilities. Because prices are largely regulated, this increase in demand is reflected primarily in higher patient volumes rather than higher prices. Higher occupancy and revenue may provide surviving facilities with additional resources to invest in staffing, regulatory compliance, or other quality-improving activities, thereby reducing deficiency citations. This mechanism is unrelated to chain acquisition and could occur regardless of changes in ownership.

Although we include county-level controls such as beds per 1,000 elderly residents, which partially capture changes in local supply, these controls may not fully account for localized exit shocks or for the timing of exits relative to acquisitions. If exits are correlated with acquisition activity or occur contemporaneously within the same markets, the observed reduction in deficiencies at acquired facilities could reflect demand reallocation following exits rather than the causal effect of chain ownership and associated efficiencies.[17]

[17] We provide more direct evidence on demand responses in Section 4.4.3, where we examine post-acquisition changes in occupancy rates, patient days, and admissions.

To control for recent facility exits, Column (4) of Table 2 includes an indicator $Exit = 1$ in our DID model of whether any facility exits occurred in the county of the focal nursing home in the previous year. The inclusion of this variable has little impact on the estimated merger effect. This suggests that the estimated effects are more likely driven by ownership-related improvements in deficiencies rather than broader market-level dynamics associated with local supply contraction.

4.3.3 Event Window

Our main results focus on the event window of a three-year period before and after mergers. Given that merger effects take years to be realized, it is interesting to examine a longer post-merger period.

Columns (5)-(7) of Table 2 report the DID results based on samples of facilities with various event windows. Column (5) extends the post-merger period to 4 years. Column (6) further restricts the sample to those with at least 4 years pre-merger, and column (7) restricts the sample even more to those with at least 5 years pre-merger. Due to more restrictive pre- and post-merger data requirements, the number of facilities is reduced significantly across alternative event windows.[18]

The DID results reported in columns (5) - (7) represent a reduction of around 0.6-0.7 units in the number of health deficiency citations after a merger takes place, which is larger than the effect reported in columns (1) and (2).

As shown in Figure 3, the merger effect emerges in the second year following the merger. By the third year post-merger, the number of health deficiency citations decreases by approximately 0.9 units. Citations remain at low levels in the fourth and fifth years after the merger, suggesting that the effect of mergers on nursing home deficiencies persists for at least five years post-merger.

4.4 Further Analyses

This section examines whether improvements in deficiency outcomes rely on continuous supply from chains post-merger and provides a falsification test to show that the effect is due to chain ownership, not ownership change. We also examine whether patient selection plays a role in explaining the observed effects on deficiencies.

4.4.1 Divestiture

To shed light on whether improvements in deficiency outcomes rely on continuous supply from chains, we consider what happens if nursing homes lose supply from their chain based on a sample of nursing homes divested/sold from chains. The treatment group now consists of nursing homes that were divested from chains. The control group is selected by matching from a pool of nursing homes that remained chain-owned for the entire study period. We applied the same empirical

[18] Compared to the baseline sample, Column (5) excludes 319 facilities. Relative to Column (5), Column (6) excludes an additional 209 facilities. Compared to Column (6), Column (7) further excludes 151 facilities. We acknowledge that the results in this section may be subject to survival bias.

methods to the divestiture sample as our merger sample and conducted both DID and event study analyses.

Column (8) of Table 2 reports the results based on a sample of facilities with an event window of a 3-year period before and after divestitures. Divestitures are associated with an increase of approximately 0.5–0.6 health deficiency citations, a magnitude comparable to the quality improvements observed following acquisitions. However, the estimate is not statistically significant.[19] Overall, these patterns suggest impact of chains partially stays with the divested facilities.

4.4.2 Chain-to-Chain Transactions

To confirm that the merger effect is due to chain ownership, not ownership change in a general sense, we consider what happens if a chain-owned nursing home gets sold to another chain. Similar to the divestiture exercise, we require that the buyers have acquired at least one independent facility during our sample period. This is to ensure we use the same set of acquirers for the chain-to-chain analysis and independent-to-chain analysis, allowing a easy comparison between the two. Using CASPER data, we identify 755 nursing homes that underwent chain-to-chain transactions conducted by the same acquirers as our main sample during the period 1999 to 2019. The treatment group now consists of previously chain-owned nursing homes that were sold to other chains. The control group is selected by matching from a pool of nursing homes that remained chain-owned for the entire study period. We applied the same empirical methods to the chain-to-chain transaction sample as our merger and divestiture sample and conducted both DID and event study analyses.

Column (9) of Table 2 reports the results based on a sample of facilities with an event window of a 3-year period before and after chain-to-chain transactions. The coefficient is positive, but statistically insignificant.[20] Our results indicate that it is chain ownership, rather than ownership change in a general sense, which is essential for improving deficiency outcomes resulting from mergers.

4.4.3 Patient Selection

In this section, we examine whether the fall in deficiencies in acquired nursing homes post-merger is confounded by selective admissions. Gandhi (2020) finds that nursing homes conduct selective admission practices that disproportionately harm Medicaid-eligible patients with lengthy anticipated stays. Cheng (2025) shows that nursing homes are more likely to reject residents with dementia, given nursing homes' complaints that they are not adequately reimbursed for such residents who tend to be more difficult to care for (Kosar et al., 2023). These residents may also exhibit behavioral issues and impose negative externalities on other residents (Cheng

[19] Consistent with this, the event study results in Figure B1(a) show no evidence of differential pre-divestiture trends, while indicating a gradual but insignificant increase in deficiency citations—particularly in the second and third years after facilities exit chain ownership.

[20] The event study results in Figure B1(b) show a mild upward trend for the coefficients with some fluctuations in the post period. However, none of these coefficients are statistically significant. Overall, there is no strong evidence supporting the causal effect of chain-to-chain transactions on health deficiency citations.

and Hackmann, 2025), which can lead to problems more easily spotted by inspectors during inspections.

To shed light on whether mergers are associated with changes in selective admissions, we analyze their effects on payer mix, occupancy rates, patient days, admissions and patient acuity index, and report the results in Columns (1)–(6) of Table 3.

First, in terms of payer mix, the share of Medicaid patients remains unchanged, while the share of Medicare patients increases significantly by 0.7 percentage points following mergers. Correspondingly, the share of private-pay patients decreases significantly. This pattern is consistent with post-merger reallocation of short-stay capacity toward Medicare patients, who typically stay for post-acute or rehabilitation care and are associated with higher and stable reimbursement rates. In contrast, private-pay residents are more exposed to financial risk if their stays are prolonged, making them relatively less attractive. Second, we find no significant change in occupancy rates. Admissions increase by approximately 7% following mergers, but total patient days remain unchanged.

Taken together, these findings suggest that the acquired facility attempts to increase revenue by adjusting their payer mix. In particular, after mergers, the acquired facility increases patient turnover by increasing the share of Medicare patients at the expense of private-pay patients. However, such patient selection does not affect the health status of admitted patients as we do not find a significant effect on the patient acuity index in column (6).

To substantiate the conclusion that the patient selection observed does not confound our main finding that health deficiency reduces after mergers, we further examine other deficiency categories, i.e. emergency preparedness (Tag E) and fire safety (Tag K) violations in CASPER, which are less likely to be affected by patient selection. Motivated by this, we conduct a DID analysis using the count of life and safety citations, including emergency preparedness and fire safety violations, as an additional outcome measure. The results are reported in column (7) of Table 3. Mergers are associated with a 0.24 reduction in the count of life and safety deficiencies, corresponding to an approximately 7% decrease relative to the sample mean of this variable (3.6). Overall, these findings are consistent with the pattern observed for health deficiencies, suggesting the limited patient selection found in Columns (1)-(5) does not confound our main results.

The following section explores the potential mechanisms underlying the merger effects on deficiency outcomes.

5 Structural Analysis

This section introduces a structural model to explain the potential mechanisms behind theeffects of mergers on health deficiency citations.

5.1 Supply Model

Nursing homes compete in quality of care for adults looking for long-term nursing home stays in year t. The assumption of quality competition is commonly employed in the literature, see Gaynor and Vogt (2000), Lin (2015), Zhao (2016) and Hackmann (2019). We assume that for-profit facilities (account for 71% in our sample) are profit maximizers; however, the rest 29% are non-profit (26%) and government facilities (3%). Although there is no specific functional form of the objective for non-profit and government facilities in nursing home literature, most papers assume a utility function that depends on profits and an additional argument such as quality (Gaynor and Vogt (2000)). Such specification assumes that those two types of nursing facilities are concerned about their quality of care in addition to profit.

We assume that nursing home j maximizes the following utility function which is additive in profits (Π_{jt}) and quality of care (q_{jt}) in year t.

$$U_{jt} = \Pi_{jt} + \lambda_{np} \cdot 1[j = nonprofit] \cdot q_{jt} + \lambda_g \cdot 1[j = government] \cdot q_{jt}$$

$1[j = nonprofit]$ and $1[j = government]$ are indicator functions that equal 1 if the nursing home is a non-profit or government facility, and 0 otherwise. Specifically, $\lambda_{np} = 0$ and $\lambda_g = 0$ for for-profit nursing homes, $\lambda_{np} \neq 0$ and $\lambda_g = 0$ for non-profit facilities, and $\lambda_{np} = 0$ and $\lambda_g \neq 0$ for government facilities.

We express nursing homes' profits as the difference between total revenue and total cost:

$$\Pi_{jt} = M_t S_{jt} \overline{LOS_{jt} R_{jt}} - C_{jt}(M_t S_{jt}, \overline{LOS_{jt}}, q_{jt})$$

where S_{jt} is market share in terms of the number of residents, $\overline{LOS_{jt}}$ is the average length of stay and M_t is the number of seniors aged 65 and above in market m. Thus $S_{jt}\overline{LOS_{jt}}M_t$ measures the total number of resident days for facility j in year t. $\overline{R_{jt}}$ denotes average per diem rate of stays in facility j in year t. A facility's total cost has three arguments, number of residents ($n_{jt} = M_t S_{jt}$), average length of stay ($\overline{LOS_{jt}}$) and quality of care (q_{jt}).

We make the following assumptions when deriving the first-order condition (FOC) of utility maximization. First, following Hackmann (2019), each resident's length of stay is known to the nursing home at the beginning of each stay. In this case, $\overline{LOS_{jt}}$ does not depend on facility j's quality of care. Second, $\overline{R_{jt}}$ does not depend on quality of care as the rate of nursing home stays is heavily regulated by government authorities.

Consider the following utility maximization problem faced by facility j acquired by a chain/acquirer in year τ_j:

$$\max_{q_j}\{U_{jt} + U_{-jt} \cdot Within_{jt} \cdot Post_{jt}\}$$

where $Post_{jt}$ is an indicator which equals 1 for $t \geq \tau_j$, and 0 otherwise. $Within_{jt}$ is an indicator that equals 1 for within-market mergers, i.e. $Within_{jt} = 1$ when the acquirer has facilities in the same county as facility j, and 0 otherwise. U_{-jt} represents the aggregated utility for the acquirer's facilities located in the same county as nursing facility j.

Deriving the FOC with respect to q_{jt} for facility j, we obtain

$$\frac{\partial U_{jt}}{\partial q_{jt}} + \frac{\partial U_{-jt}}{\partial q_{jt}} Within_{jt} \cdot Post_{jt} = 0$$

where

$$\begin{aligned}
\frac{\partial U_{jt}}{\partial q_{jt}} &= MR_{jt} - MC_{jt} + \lambda_{np} \cdot 1[j = nonprofit] + \lambda_g \cdot 1[j = government] \\
&= \frac{\partial S_{jt}}{\partial q_{jt}} M_t \overline{LOS}_{jt} R_{jt} - \frac{\partial C_{jt}}{\partial n_{jt}} \frac{\partial S_{jt}}{\partial q_{jt}} M_t - \frac{\partial C_{jt}}{\partial q_{jt}} \\
&\quad + \lambda_{np} \cdot 1[j = nonprofit] + \lambda_g \cdot 1[j = government]
\end{aligned}$$

There are two components of $\frac{\partial U_{jt}}{\partial q_{jt}}$ that deserve discussion. $MR_{jt} = \frac{\partial S_{jt}}{\partial q_{jt}} M_t \overline{LOS}_{jt} R_{jt}$ measures the marginal revenue of quality improvement. To be specific, one unit of quality improvement attracts $\frac{\partial S_{jt}}{\partial q_{jt}} M_t$ more residents, which generates $\frac{\partial S_{jt}}{\partial q_{jt}} M_t \overline{LOS}_{jt}$ more resident days and hence increases revenue for the facility. $MC_{jt} = \frac{\partial C_{jt}}{\partial n_{jt}} \frac{\partial S_{jt}}{\partial q_{jt}} M_t + \frac{\partial C_{jt}}{\partial q_{jt}}$ measures the marginal cost of quality improvement. On the one hand, the marginal cost of serving residents increases (measured by $\frac{\partial C_{jt}}{\partial n_{jt}} \frac{\partial S_{jt}}{\partial q_{jt}} M_t$) as the facility attracts more residents due to its improved quality. On the other hand, quality improvement imposes additional costs on the facility (measured by $\frac{\partial C_{jt}}{\partial q_{jt}}$).

There are three terms that need to be specified in order to fully specify MR_{jt} and MC_{jt}. First, we employ a discrete choice demand model for differentiated products of Berry (1994). $\frac{\partial S_{jt}}{\partial q_{jt}}$ takes the following form:

$$\frac{\partial S_{jt}}{\partial q_{jt}} = \frac{a}{1-\sigma}\left[1 - \sigma S_{jt|g} - (1-\sigma) S_{jt}\right] S_{jt} = \kappa_{jt} S_{jt}$$

where $\kappa_{jt} = \frac{a}{1-\sigma}[1 - \sigma S_{jt|g} - (1-\sigma) S_{jt}]$. The variable $S_{jt|g}$ is the market share of facility j among all sample nursing facilities in its market at period t. The parameters a and σ are demand parameters, see Appendix C for the details of model specification and estimation.

Second, we specify the following functional forms for the marginal cost functions:

$$\begin{aligned}
\frac{\partial C_{jt}}{\partial q_{jt}} &= \delta_{0q} + \delta_{qn} n_{jt} + \delta_{qw} w_{jt} + \delta_{qL} \overline{LOS}_{jt} + \delta_{qp} post_{jt} \\
\frac{\partial C_{jt}}{\partial n_{jt}} &= \delta_{0n} + \delta_{nq} q_{jt} + \delta_{nw} w_{jt} + \delta_{nL} \overline{LOS}_{jt} + \delta_{np} post_{jt}
\end{aligned}$$

We include merger indicators in the marginal cost functions to account for the potential cost savings from mergers. Specifically, δ_{np} reflects the potential savings on the marginal cost of serving residents and δ_{qp} reflects the potential savings on the marginal cost of quality provision. These two parameters represent the potential cost efficiencies of mergers discussed in the theoretical framework. These cost savings might be passed on to nursing home residents in the form of a higher quality of care after mergers.

Finally, to specify $\frac{\partial U^{-jt}}{\partial \ _{jt}}$, we notice that for each merger in our sample we can identify whether it is a within-market or cross-market transaction, since CASPER covers nearly all nursing homes in the United States. However, revenue and wage data are drawn from HCRIS, which includes only skilled nursing facilities (SNFs). As a result, even when we identify within-market mergers, we may lack the information necessary to estimate $\frac{\partial U^{-jt}}{\partial \ _{jt}}$ for facilities not captured in HCRIS. For this reason, we specify $\frac{\partial U^{-jt}}{\partial \ _{jt}} = \gamma$ to capture the market-power incentive for quality reduction. This channel is relevant only for within-market mergers (accounts for 30% of our sample mergers) in which the acquirer operates facilities in the same county as facility j. In such cases, an increase in facility j's quality reduces the aggregate utility of other facilities owned by the acquirer, which undermines facility j's incentive to improve its quality.

Rewrite the FOC using our specifications for various derivatives and rearrange the equation, we obtain the following quality supply equation:

$$
\begin{aligned}
q_{jt} = & \frac{1}{\delta_{nq}} \left(LOS_{jt} \cdot R_{jt} - \ _{jt} \right) - \frac{\delta_{0q}}{\delta_{nq}} \frac{1}{\kappa_{jt} n_{jt}} - \frac{\delta_{qn}}{\delta_{nq}} \frac{1}{\kappa_{jt}} - \frac{\delta_{qw}}{\delta_{nq}} \frac{w_{jt}}{\kappa_{jt} n_{jt}} - \frac{\delta_{qL}}{\delta_{nq}} \frac{\overline{LOS_{jt}}}{\kappa_{jt} n_{jt}} - \frac{\delta_{nw}}{\delta_{nq}} w_{jt} - \frac{\delta_{nL}}{\delta_{nq}} LOS_{jt} \\
& + \frac{\lambda_{np}}{\delta_{nq}} \cdot \frac{1[j = nonprofit]}{\kappa_{jt} n_{jt}} + \frac{\lambda_{g}}{\delta_{nq}} \cdot \frac{1[j = government]}{\kappa_{jt} n_{jt}} \\
& - \frac{\delta_{np}}{\delta_{nq}} post_{jt} - \frac{\delta_{qp}}{\delta_{nq}} \frac{1}{\kappa_{jt} n_{jt}} \cdot post_{jt} + \frac{\gamma}{\delta_{nq}} \frac{Within_{jt}}{\kappa_{jt} n_{jt}} \cdot post_{jt} - \frac{\delta_{0n}}{\delta_{nq}} + \ _{jt}
\end{aligned}
\tag{3}
$$

where the error term $_{jt}$ is the measurement error of quality.

One advantage of using the structural model is to recover the potential mechanisms behind quality improvement. Specifically, the quality supply equation (3) contains three terms, namely $-\frac{\delta_{np}}{\delta_{nq}} - \frac{\delta_{qp}}{\delta_{nq}\kappa_{jt}n_{jt}} + \frac{\gamma}{\delta_{nq}\kappa_{jt}n_{jt}}$ to reflect the overall marginal effect of quality for within-market mergers. We call the first term, $-\frac{\delta_{np}}{\delta_{n}}$ as Cost Efficiency as it relates to δ_{n} (parameter for $post_{jt}$ in the $\frac{\partial C_{jt}}{\partial n_{jt}}$ function), i.e. the effect of merger on marginal cost of serving an additional resident $\frac{\partial C^{jt}}{\partial n_{jt}}$. We call the second term, $-\frac{\delta_{qp}}{\delta_{nq}\kappa_{jt}n_{jt}}$ as Quality Cost Savings, as it relates to δ_{q} (parameter for $post_{jt}$ in the $\frac{\partial C^{jt}}{\partial q_{jt}}$ function), i.e. the effect of merger on marginal cost of quality provision $\frac{\partial C^{jt}}{\partial q_{jt}}$. We call the third term, $\frac{\gamma}{\delta_{nq}\kappa_{jt}n_{jt}}$ as Market Power as it relates to γ, i.e. the market power effect of merger $\frac{\partial U^{-jt}}{\partial q_{jt}}$.

In summary, the supply model allows us to decompose the overall effect into three components: Cost Efficiency, Quality Cost Savings, and Market Power. While both the Cost Efficiency and Quality Cost Savings components provide incentives for nursing homes to enhance the quality of care, the Market Power component encourages a reduction in quality.

5.1.1 Estimation

We estimate the quality supply equation (3) using information on the total number of patient days, nursing staff wage and nursing home revenue data available in the HCRIS database. The outcome variable is count of health deficiency citations.

Because the Quality Cost Savings $-\frac{\delta_{qp}}{\delta_{nq}\kappa_{jt}n_{jt}}$ and Market Power $\frac{\gamma}{\delta_n}\frac{Within_{jt}}{\kappa_{jt}n_{jt}}$ components vary across different facilities, these two components are evaluated at the sample mean of $\frac{1}{\kappa_{jt}n_{jt}}$ and $\frac{Within_{jt}}{\kappa_{jt}n_{jt}}$. Accordingly, the reported estimates correspond to the average facility.

One potential endogeneity problem arises from $\overline{R_{jt}}$. Most states currently employ a prospective payment system in which the Medicaid and Medicare reimbursement rates are predetermined based on historical cost data (Lin, 2015). However, if there is a persistent component of cost, such as staffing intensity, management practices, or underlying quality choices, then past costs will be correlated with current unobserved determinants of quality. In addition, 27% of the residents have private payers.[21] The private rate is set by the nursing home alone and it depends on the quality of care provided to residents.

We use two sets of instrument variables for revenue per resident, $\overline{R_{jt}} \cdot \overline{LOS_{jt}}$. One set of instruments follows the spirit of Hackmann (2019) to isolate parts of the reimbursement schedule that depends on lagged values of other non-competing (nc) nursing homes' characteristics: $Medicaid_{nc,t-1}$, and $wage_{nc,t-1}$, where non-competing nursing homes are defined as facilities located outside the focal nursing home's county and within a 50–100 km radius (i.e., in a surrounding "donut" area) of the focal facility.[22] Medicaid share $Medicaid_{nc,t-1}$ reflects broader Medicaid generosity, state level eligibility rules and regional payer mix shifts, while $wage_{nc,t-1}$ reflect regional labor market conditions. These variables are correlated with the reimbursement schedule, while geographic separation and lagged values reduce concerns that these variables directly affect the quality of the focal facility.

The second set of instruments utilizes facilities' differential exposure to state Medicaid reimbursement rates:

$Medicaid_{it-1} \times StateMcaidRate_{st}$ and $Medicaid_{it-1} \times (StateMcaidRate_{st} - StateMcaidRate_{st-1})$ where $StateMcaidRate_{st}$ is calculated as state Medicaid nursing facility expenditure divided by state nursing home days.[23] These instruments reflect state level policy variations that are not directly correlated with the facility nursing home's quality choice. Both sets of instruments exploit the variations of reimbursement-driven changes in revenue per resident to identify δ_{nq}. Encouragingly, both sets of instruments pass the weak instrument test, with the first-stage Kleibergen–Paap

[21] According to Hackmann (2019), the majority of the residents with private payers pay out-of-pocket for their nursing home stays as opposed to private health insurance.

[22] Specifically, Hackmann (2019) exploits the lagged average costs and characteristics of other nursing homes in the same peer group (defined by size and region) but in different counties to instrument nursing home reimbursement in Pennsylvania, given that reimbursement depends on own average costs as well as average costs of nursing homes in the same peer group.

[23] State-level Medicaid nursing facility expenditure data are obtained from CMS Medicaid Long-Term Services and Supports expenditure reports. Total state nursing home days are constructed as the sum of resident days across all nursing homes within each state.

rk F-statistics exceeds the conventional threshold of 10.

There is a limitation of our IV strategy that deserves a discussion. Recent evidence (Einav et al., 2025) suggests a potential negative relationship between nursing home quality and length of stay. This causes a potential endogeneity issue in the length of stay, which may not be fully eliminated with our IV. The negative relationship between quality and length of stay may bias downward the coefficients of variables involving $\overline{LOS_j}$: $\frac{1}{\delta_n}$, $-\frac{\delta_{qL}}{\delta_n}$ and $-\frac{\delta_{nL}}{\delta_n}$. As a result, there is a potential upward bias in δ_{nq} (the effect of quality on the marginal cost of serving patients), δ_{qL} (the effect of LOS on the marginal cost of quality provision) and δ_{nL} (the effect of LOS on the marginal cost of serving patients). Intuitively, quality becomes less responsive to LOS. The model therefore infers a higher cost of providing quality through length of stay.

Turning to Equation (3), our focus is the effect of merger on quality provision, or $-\frac{\delta_{np}}{\delta_n} - \frac{\delta_{qp}}{\delta_{nq}\kappa_{jt}n_{jt}} + \frac{\gamma}{\delta_{nq}\kappa_{jt}n_{jt}}$, where the first term is cost efficiency, the second term is quality cost savings and the third term is market power. The potentially biased parameters may lead to an underestimation of all three components. With the discussion above, the negative relationship between quality and average length stay would lead to underestimation of the merger effects, suggesting that our estimates are conservative.

5.2 Decomposition

Table 4 shows the overall effect of mergers on health deficiencies and its decomposition for the two DID samples of our main focus, -3 to +3 and -3 to +4. Columns (1) and (3) report the estimates using non-competing nursing home characteristics as instruments, and columns (2) and (4) report the estimates using facilities' differential exposure to state medicaid reimbursement rates as instruments. These results indicate a significant reduction in health deficiency citations of around 0.5-0.6 units in the 3 years following mergers, and a larger reduction of around 0.7 units 4 years post-merger. The results are robust across alternative instrument specifications. Encouragingly, our structural estimation aligns closely in magnitude with our Difference-in-Differences estimation results presented in Table 2.

By decomposing the overall effect into three components, we notice that the Cost Efficiency component significantly dominates that other components. This implies that mergers reduce deficiencies primarily through savings on the marginal cost of serving residents. In contrast, the Quality Cost Savings component remains insignificant across all specifications, suggesting that it is difficult for chains to lower the marginal cost of quality provision. Unlike operational efficiencies in routine service delivery, quality-related inputs cannot be easily scaled down, particularly given that the health deficiencies of our focus are closely tied to minimum staffing standards, regulatory compliance requirements, and clinical protocols. As a result, nursing homes have limited flexibility to reduce the marginal cost of quality provision without incurring regulatory risk or compromising care standards. Turning to the Market Power component, we find that it becomes only marginally significant when the analysis is extended to a four-year post-merger period, implying limited incentives for facilities within the same chain to coordinate their quality decisions following a merger. However, only one-third of the mergers in our sample are within-market mergers. As a result, the estimated market power effect represents the average effect across within-market mergers (market power > 0) and cross market mergers (market power = 0). We report the marginal effects separately for within-market and cross-market mergers in section 5.3.1.

5.3 Heterogeneity

In this section, we investigate whether mergers generate heterogeneous effects across subgroups of nursing homes. We focus on the structural estimation, which enables us to characterize how the three components vary across these subgroups.[24] The reduced-form results, reported in Appendix B, Table B2, exhibit consistent patterns.

The heterogeneity analysis starts with within- vs. cross-market mergers, and the effects are reported using full-sample parameter estimates. This is because restricting the sample to only within-market or only cross-market mergers would prevent identification of the market power effect. Since marginal effects vary across different facilities, the relevant components are evaluated at the sample mean within each subsample.

For the latter three heterogeneity analyses, namely large vs. small chain, low vs. high deficiency chain, and high vs low staffing chain, we rely on subsample estimation. In those cases, we estimate the model separately within each subsample and evaluate effects at the corresponding subsample means.

5.3.1 Within- vs. Cross-Market

Within-market mergers might be driven by the market-power motive, which creates an incentive for quality reduction as opposed to quality improvement after mergers. This is not the case for cross-market mergers which mainly happen for market expansion purposes. We utilize the structural model to identify the market power component for within-market mergers using the interaction term $\frac{W\ ithin_{jt}}{\kappa_{jt} n_{jt}} \cdot post\ _j$ in equation (3).

Columns (1) and (2) of Table 5 report the decomposition estimates for within-market and cross-market mergers. Here again, markets are defined at county level.[25] Across both event windows, the market power component is positive. The interpretation is that reduced local competition incentivizes the acquired facilities to increase health deficiencies post-merger by around 0.2-0.5 units. The market power effect is not statistically significant for the −3 to +3 sample. However, when the analysis is extended to a longer post-merger horizon of four years, the market power effect becomes marginally significant, and its magnitude (0.532) is close to that of the cost-efficiency component (0.754). These results suggest that market power incentive may potentially offset the deficiency reduction associated with cost efficiency. As a result, the net effect is a substantially

[24]Note that the analyses in this section are using non-competing nursing home characteristics as instruments. Using differential exposure to state Medicaid reimbursement rates as instruments produces similar results. The results are available upon request.

[25]Using core-based statistical area (CBSA) as markets has minimal impact on our results.

smaller decrease in health deficiencies for within-market mergers compared to cross-market mergers in the reduced-form estimation (see columns 1 and 2, Table B2).

The above analysis is based on the assumption of $\frac{\partial U^{-jt}}{\partial \ _{jt}} = \gamma$. However, this market-power effect may vary with market concentration, as the incentive to compromise quality for profit is likely to be larger for more concentrated markets. Accordingly, we estimate an alternative specification in which $\gamma = \gamma_1 + \gamma_2 \cdot HighHHI$, where $HighHHI = 1$ for markets with HHI greater than 1500 following the merger guidelines from the Federal Trade Commission (FTC).[26] The results are presented in Appendix B, table B3. The effect of the interaction term $MarketPower \times HighHHI$ is insignificant, which suggests that the difference in market power effect between concentrated markets and non-concentrated markets is insignificant.

5.3.2 Large vs. Small Chain

Second, we explore the heterogeneous effects of nursing home mergers initiated by large versus small chains. We define a small chain as a chain owning fewer than 5 facilities, which is consistent with the definition used in Grabowski et al. (2016). For this heterogeneity analysis, the results are based on a subsample analysis.

Columns (3) and (4) of Table 5 report the decomposition of merger effects for the large-chain and small-chain subsamples, respectively. Mergers initiated by small chains are associated with a statistically significant reduction in health deficiencies of approximately 0.8 units across various post-merger windows. This decline is primarily driven by the cost efficiency component, or a reduced marginal cost of serving patients post merger. In contrast, mergers involving large chains do not reduce health deficiencies significantly at acquired facilities.

In sum, we find smaller chains are more able to improve cost efficiency after mergers. For small chains, which in our sample operate on average approximately two facilities (see Table 1 Panel A). With this small size, they may not able to derive cost efficiency from better capacity utilization (Lynk, 1995) or consolidation of duplicate administrative functions (Schmitt, 2017). Alternatively, they may derive cost efficiency from a "turn around" logic (Banaszak-Holl et al., 2002) wherein chains attempt to improve the performance of targeted homes through their superior management skills. This mechanism speaks to the management turnover hypothesis discussed in the subsection of theoretical framework. In contrast, the absence of cost efficiency effects for large chains may reflect diminishing marginal returns to further scale. The large chains in our sample on average operate 30 facilities (see Table 1 Panel A). For these larger systems, coordination costs, communication frictions, and administrative layering can limit the scope of reductions in the marginal costs of serving patients.

[26] FTC defines markets with $HHI < 1500$ as non-concentrated markets, and markets with $HHI > 2500$ as highly concentrated markets.

5.3.3 Low vs. High Deficiency Chain

Next, we explore the heterogeneous effects of nursing home mergers involving low-deficiency versus high-deficiency chains. Columns (5) and (6) of Table 5 report the decomposition analysis for the low- and high-deficiency subgroups, respectively. Mergers initiated by low-deficiency chains are associated with a significant (at 1% level) reduction of 1 unit in the number of health deficiency citations over a three-year period post-merger. This effect is driven primarily by the cost efficiency component, while the other two components are small in magnitude and statistically insignificant. Turning to mergers involving high deficiency chains, we noticed no significant effects across any component within the three-year event window. When we extend the analysis to a four-year post-merger period, the market power component becomes positive and statistically significant for high deficiencies chains. Not surprisingly, high-deficiency chains rely more heavily on exercising market power to realize the benefits of mergers.

The observation that the reduction in health deficiencies are concentrated among mergers involving low-deficiency chains likely reflects that these chains have established best practices and standardized compliance management processes that can be transferred to acquired facilities, consistent with the second source of cost efficiency described in the theoretical framework.

5.3.4 High vs. Low Staffing Chain

We conduct a subsample analysis of mergers involving high-staffing chains versus those involving low-staffing chains. This analysis helps to inform whether compliance know-how or staffing improvement drives the deficiency reduction after mergers.[27]

We use direct care nurse hours per resident day to classify chains into high- and low-staffing groups. In our sample, the median direct care hours is approximately 3.31 hours per resident day, which is used as the cutoff for defining high- and low-staffing chains. Columns (7) and (8) of Table 5 report the decomposition results for the high- and low-staffing subsamples, respectively. Unlike the subsample analysis comparing low- and high-deficiency chains, where the effects are concentrated among low-deficiency chains, both high- and low-staffing groups exhibit reductions in deficiencies following mergers. Further, when extending the event window to a four-year post period, the cost efficiency component is significant at the 10 percent level for both sub-samples.

Combining the results of these two sub-sections, the deficiency reduction after mergers seems to be driven by compliance management rather than staffing (a proxy of quality) improvement.

5.4 Cost Effects of Merger

The structural model suggests that the observed reduction in deficiencies is driven primarily by cost efficiencies, i.e. a lower marginal cost of serving patients after mergers. In this subsection, we verify these results by estimating equation (2) using the logarithm of inpatient routine service cost per resident as the outcome variable. On average, the cost of inpatient routine services accounts

[27] More discussion is available in section 6

for 82% of the total facility cost in our sample. This encompasses expenses related to regular room occupancy, dietary and nursing services, minor medical and surgical supplies, as well as the utilization of equipment and facilities. The event study analysis presented in Figure 4 indicates that reductions in inpatient routine costs begin to emerge in the year of the merger and they persists for at least four years. The coefficients for $1[i \in T, t = \tau_i + k, k >= 1]$ are statistically significant at the 5% level in the sample with a three-year event window, and they become significant at the 1% level when using a four-year event window. Compared to the cost one year prior to the merger, inpatient routine cost per resident declines by more than 3% by the fourth year following mergers.[28]

6 Staffing and Health Outcomes

The previous sections find a significant reduction in the number of health deficiency citations at acquired facilities following mergers. Here, we explore how mergers affect staffing outcomes and residents' health outcomes. The objective is to shed some light on whether the decline in deficiency citations translate into better quality of care after merger.

6.1 Staffing Outcomes

Staffing is the dominant input in the production of nursing home services, particularly direct care staffing, which includes registered nurses (RNs), licensed practical nurses (LPNs), and certified nursing assistants (CNAs). These workers are central to the day-to-day provision of resident care. Staffing levels and composition determine how frequently residents are attended to, the amount of time caregivers can devote to individual needs, and the extent to which both routine and non-routine care tasks can be completed.

RNs, LPNs, and CNAs differ in their educational requirements and scopes of practice.[29] RNs have the highest level of training and clinical responsibility, including complex assessment and care planning, clinical oversight, and supervision of other nursing staff, whereas LPNs provide intermediate-level care under RN supervision with a more limited scope of practice. CNAs primarily assist with residents' activities of daily living. Nonetheless, the existing literature shows

[28] We also estimate the DID model and find that this cost per resident is reduced by 1.1% at 10% significance level in a three-year period after mergers, and by 1.6% at 5% significance level in a four-year period post-merger.

[29] To become an RN, individuals must complete either an Associate or Bachelor of Science in Nursing program (typically 3–4 years) or a three-year hospital-based diploma program, followed by passing the national licensing examination. RNs have a substantially broader scope of practice than LPNs and CNAs. They are typically responsible for clinical assessments, care planning, and clinical oversight, and they often delegate tasks to LPNs and CNAs while assuming supervisory responsibilities.

LPNs are required to complete a vocational or community college–based practical nursing program, which generally takes 1–2 years, and pass a licensing exam. While LPNs can perform certain clinical procedures, their responsibilities are more limited than those of RNs.

CNAs constitute the largest share of the direct care workforce and provide most hands-on assistance to residents, including help with bathing, dressing, transferring, and feeding. Training requirements for CNAs vary by state, but federal minimum standards under the Nursing Home Reform Act generally require at least 75 hours of training, including 16 hours of supervised clinical instruction.

that a higher level of various types of nurse staff improves quality delivered by nursing homes (Lin (2014); Gandhi et al. (2025)).

Columns (1) to (3) in Panel A of Table 6 report that the share of LPN hours increases significantly by 0.514 percentage points following mergers, whereas the shares of RN and CNA hours decline by 0.247 and 0.282 percentage points, respectively. These patterns suggest that mergers reshape the composition of the nursing workforce, shifting the skill mix toward a greater reliance on LPNs.

To capture the overall effect on the amount of care provided to patients, we examine direct care hours, measured in hours per resident day. Column (4) finds that direct care hours decline by approximately 0.122 hours following mergers, corresponding to a 3.5% reduction relative to the sample mean of 3.483 hours. Further, to examine the overall effect on skilled care provided to patients, we aggregate LPN and RN hours and report the effect on total skilled nurse hours in column (5).[30] The skilled nurse hours per resident day is reduced by 0.0251 hours after mergers, representing a 2% reduction relative to the mean of this variable.

One concern with staffing measures is that they may be subject to misreporting or strategic gaming by nursing homes. Recent studies (Geng et al. (2019) and Chen and Dillender (2025)) document sharp changes in reported staffing levels in the weeks surrounding inspection visits. More reliable staffing data from the Payroll Based Journal (PBJ) only became available in 2017, so there is not enough data to conduct the same event study analysis. Nonetheless, we collect 2017-2019 PBJ data and restrict the sample to nursing homes for which discrepancies in skilled nurse hours between PBJ staffing and CASPER are small.[31] The results, reported in column (6), are consistent with column (5), showing a reduction in skilled nurse hours following mergers, although the estimate is not statistically significant.

As discussed in the previous sections, a potential mechanism behind the decline in health deficiency citations is the reduction in the marginal cost of serving patients following mergers. Taken together, the staffing results suggest that the cost decline is likely attributed to reduced nurse staffing hours, accompanied by an adjusted mix of nursing inputs after the merger.

6.2 Severity of Health Deficiencies

With a reduction in direct care hours after mergers, we next ask whether the decline in deficiency citations reflects simply better compliance management or more meaningful clinical improvement. Geng et al. (2019) and Chen and Dillender (2025) showed sharp changes in nursing home staffing and practices in the few weeks surrounding inspectors' arrivals, and that the extent of these

[30]This measure is also the primary quality measure in Hackmann (2019)

[31]For each nursing home in our sample with observations during 2017–2019, we extract Payroll-Based Journal (PBJ) data for the two-week period preceding its annual survey date. We calculate payroll-reported skilled nurse hours by summing the reported hours for registered nurses (RNs) and licensed practical nurses (LPNs). Payroll-reported skilled nurse hours per resident day are then calculated by dividing the total skilled nurse hours by the aggregate resident census over the same two-week period. We compare this measure with the skilled nurse hours per resident day obtained from CASPER. For each facility-year, we calculate the percent difference between the two measures and then average these differences across all available years (2017–2019) for each facility. The PBJ validation sample includes facilities whose average absolute percent difference in skilled nurse hours per resident day between CASPER and PBJ is less than 10%.

strategic responses varies with nursing home characteristics. They find that for-profit nursing homes exhibit larger responses, but they do not examine the role of chains.

To address this question, we decompose deficiency citations by scope and severity (Tags A-L in the CASPER data). If the reduction concentrates on harm-level citations (Tags G and above), the quality improvements are more likely to reflect meaningful changes in resident care. In contrast, if the reduction concentrates on lower-severity or administrative citations (Tags A–F), the observed effects are more consistent with improved compliance management or the correction of simple procedural deficiencies.

We focus on a subsample of mergers covering years 2009-2019 (consisting of 275 mergers that occurred between 2012 and 2016), for which scope and severity information on health deficiencies is available to us. Column (1) of Table 7 reports the DID analysis for this subsample. The results are consistent with those reported in column (2) of Table 2. Specifically, among the 275 mergers occurring between 2012 and 2016, deficiency citations decrease by 0.592 citations following a merger. Facilities in this subsample exhibit fewer health deficiency citations on average (5.499) than facilities in the full sample (6.164). As a result, a reduction of 0.592 citations corresponds to an approximately 11% decline relative to the mean.

We next decompose deficiencies into low-severity citations (Tags A–F) and high-severity citations (Tags G and above). Facilities acquired by nursing home chains in this subsample are predominantly homes with only low-severity deficiencies. On average, facilities have 0.144 high-severity deficiencies, compared to 5.322 low-severity deficiencies. Columns (2) and (3) report that the estimated merger effect is statistically significant only for low-severity citations, indicating that the post-merger reduction in health deficiencies is driven primarily by fall in low-severity deficiencies.

Together, these findings suggest that the observed decline in deficiency citations is more likely driven by improved compliance management than by reduced harm-level citations. One possibility is that independent nursing homes acquired by chains become more adept at responding to inspections and thus receive fewer deficiency citations despite quality provision for harm reduction remaining unchanged.

6.3 Health Outcomes

The previous section documents a significant reduction in direct care staffing post-merger. Although there is general agreement that direct care staffing is a key determinant of quality, there is no consensus on optimal staffing levels and skill mix (Gandhi et al., 2025).[32] To evaluate whether the staffing reductions observed after mergers coincide with worse resident health, we now examine whether mergers are associated with changes in patient health outcomes. Specifically, we employ five health outcomes in the spirit of Grabowski et al. (2008) and Antwi and Bowblis (2018).

The first two measures focus on the share of residents with pressure ulcers (*bedsores*) and those

[32] The existing literature suggests a mixed relationship between nursing home staffing and quality of care. See Clemens et al. (2021) for a recent review.

with contractures (*contract*). Pressure ulcers emerge from skin and tissue injuries due to a lack of blood supply induced by constant pressure, and contracture is a shortening of soft tissue caused by the lack of movement of a joint. Both of these conditions are preventable and treatable, making them important indicators of the quality of care provided. The second two measures focus on the share of residents with urethral catheters (*catheter*) and those with physical restraints (*restrain*). The implementation of these care practices exposes residents to elevated medical risks, including the potential for urinary tract infections resulting from the former and the risk of pressure ulcers arising from the latter. The fifth measure is unplanned weight change (*loss*), which is a prognostic indicator reflecting potential disease progression.

Panel B of Table 6 presents the results of equation (1) using the five health measures as outcome variables. All five measures have negative coefficients for $1[i \in T, t \geq \tau_i]$, but only one measure shows significant effects. The percentage of residents with contractures is reduced by 2.464 percentage points at 1% significance level, representing a 8.8% decrease from the average of 27.87. To aggregate the effects of nursing home mergers on residents' health outcomes, we report the results of equation (1) using a summary index of the above five quality measures as the outcome variable, following the approach of Finkelstein et al. (2012). The summary index is calculated as the equally weighted average of z-scores of its five components.[33] As shown in column (6) of Panel B in Table 6, the coefficient of $1[i \in T, t \geq \tau_i]$ is negative and significant at 1% level, driven largely by a reduction in contractures.

The decline in direct care hours following mergers may explain why we do not observe improvements in health outcomes that depend on frequent and active care, such as pressure ulcer prevention (frequent repositioning) and preventing catheter use (regular toileting scheduling). Nonetheless, mergers appear to improve outcomes that require less continuous direct care, such as contracture prevention, which can be addressed through less labor-intensive interventions such as splinting.

7 Conclusion

This paper evaluates the quality effects of nursing home mergers. Using a staggered DID approach, we find a nearly 8% reduction in the number of health deficiency citations for acquired facilities in the years following mergers. We observe no clear evidence of patient selection confounding our main results, with the exception of higher turnover among Medicare patients. A structural model reveals that the driving force behind the improvement in deficiencies is the enhanced cost efficiency achieved from a lower marginal cost of serving residents after mergers. The cost saving is more pronounced for cross-market mergers and mergers initiated by smaller, or lower-deficiency chains. However, this cost efficiency is accompanied by a decline in direct care hours, alongside a shift in staffing composition toward greater reliance on licensed practical nurses. Furthermore,

[33] Each z-score is derived by subtracting the control group mean from the corresponding measure and dividing by the control group standard deviation.

the reduction in deficiencies is concentrated entirely in low-severity categories, suggesting that mergers improve regulatory compliance rather than true clinical outcomes. Consistently, we find no meaningful impact of mergers on residents' health outcomes.

Our results highlight several implications related to antitrust policies for mergers in the nursing home industry, especially about the ongoing discussions on lowering the thresholds for determining a merger to be presumptively anticompetitive and limiting cross-market mergers in the 2023 Draft Merger Guidelines.[34] First, quality of care does not improve in mergers initiated by large chains. In contrast post-merger reductions in regulatory deficiencies are driven primarily by acquisitions initiated by smaller and low-deficiency chains. This suggests that antitrust frameworks should incorporate a more nuanced review process: while acquisitions by large chains warrant investigation, acquisitions by smaller, high-compliance chains may facilitate the transfer of effective administrative and compliance protocols to independent facilities. Second, policy makers have been becoming more attentive to cross-market mergers in the healthcare industry.[35] However, our study reveals the positive quality effect is weaker for within-market mergers than for cross-market mergers. Antitrust concerns on nursing home industry consolidation should still prioritize scrutiny of within-market mergers over cross-market mergers, at least for the nursing home industry.

[34] See https://www.justice.gov/atr/d9/2023-draft-merger-guidelines

[35] In the hospital sector, they expressed concerns about potential increases in prices for consumers caused by cross-market mergers. See Dafny et al. (2019) and the references therein.

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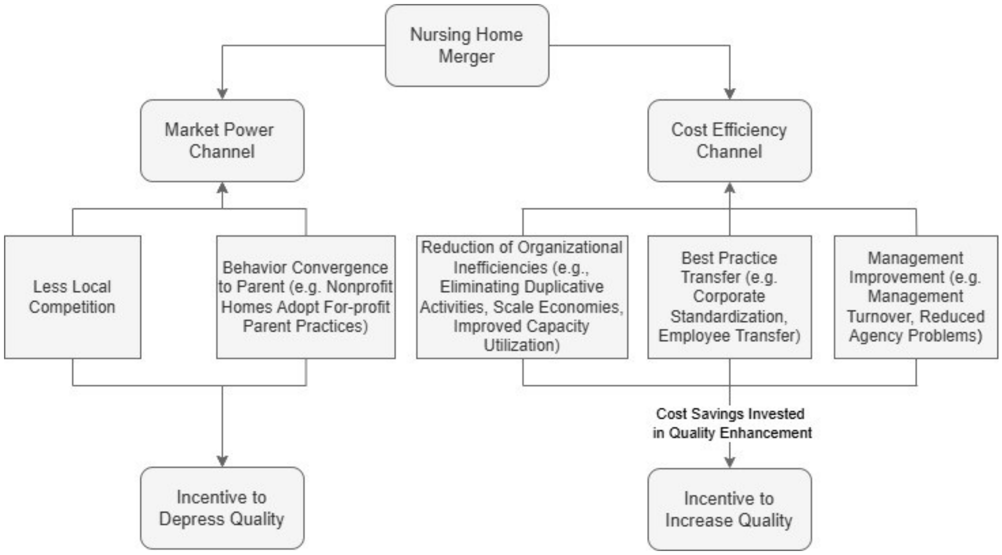


Figure 1: Nursing Home Mergers: Two Channels Affecting Quality

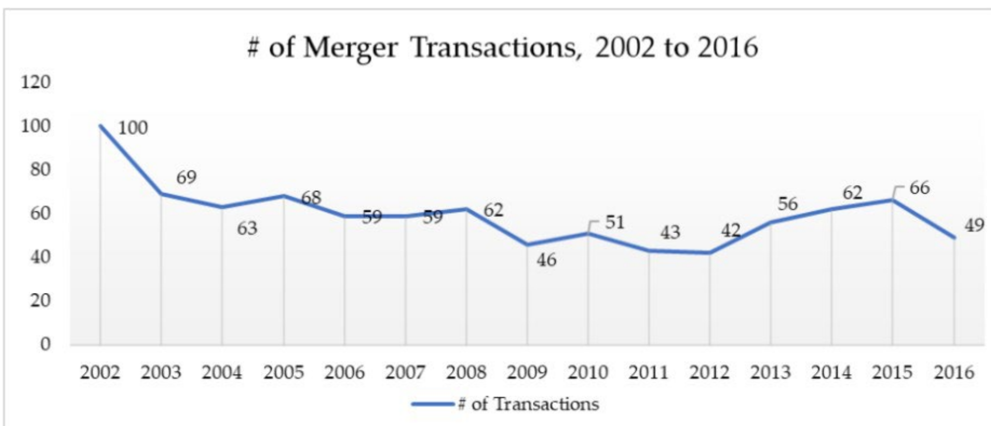


Figure 2: Number of Merger Transactions, 2002 to 2016

Data Source: Authors' analysis of CASPER & HCRIS data. The study period of this paper is 1999 to 2019. However, since we require facilities to have three years of data prior to being acquired and three years of data after being acquired, only merger transactions that happened between 2002 and 2016 are captured in our analysis.

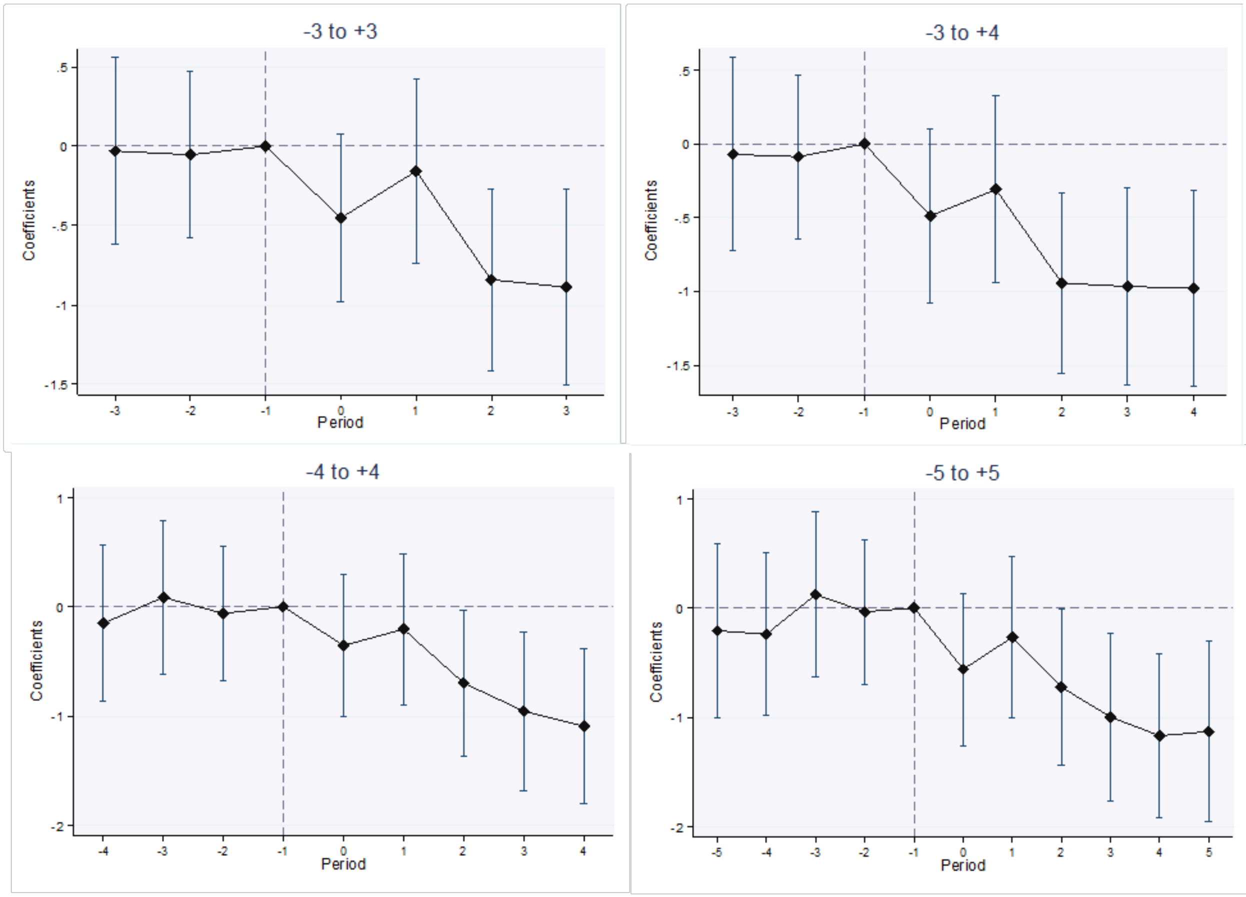


Figure 3: Effects of Merger on Health Deficiencies
Notes: This figure presents coefficient plots of event study regressions based on equation (2). The outcome variable is count of health deficiency citations.

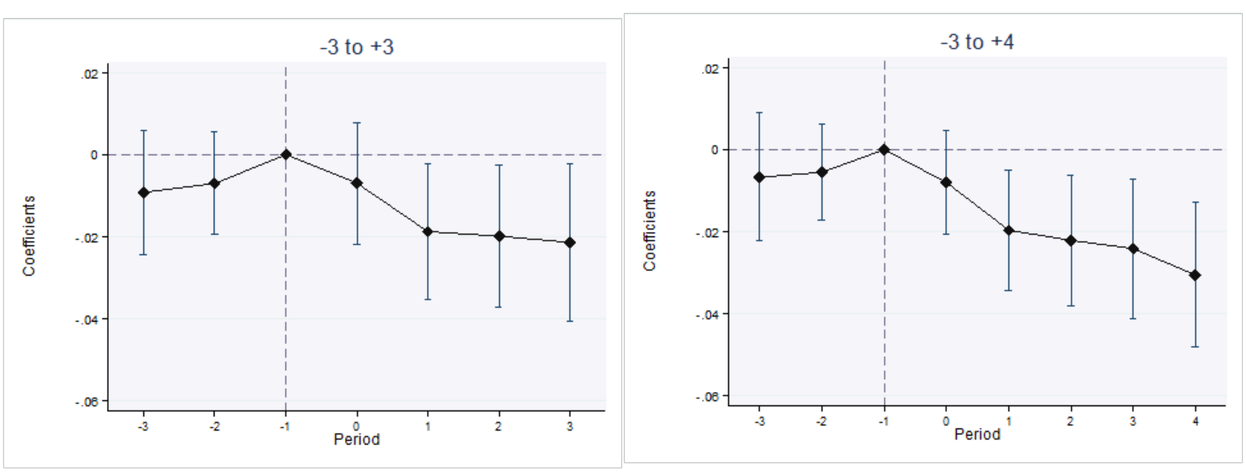


Figure 4: Effects of Merger on log of Cost Per Resident
Notes: This figure presents coefficient plots of event study regressions based on equation (2). The outcome variable is logarithm of inpatient routine cost per resident.

Table 1: Summary Statistics

Panel A: Transaction Level Statistics

Merger Type	(1) N Transactions	(2) Avg. Acquirer Size
Within-Market	256	23
Cross-Market	639	12
Large Chain	411	30
Small Chain	484	2
Low Deficiency	450	12
High Deficiency	445	18
High Staffing	447	12
Low Staffing	448	19
Total N Transactions	895	15

Panel B: Facility Level Statistics

Variable	(1) Full Sample	(2) Acquired	(3) Matched Control
Outcome Variable			
count of health deficiencies	6.164	6.368	5.949
Facility Characteristics			
nonprofit	0.275	0.270	0.281
government	0.033	0.030	0.036
% Medicaid	60.371	59.557	61.224
% Medicare	13.241	13.847	12.606
total beds	112.421	112.951	111.865
acuity index	11.470	11.500	11.438
special care unit	0.225	0.231	0.218
wage	15.619	15.595	15.644
Total N Observations	12,243	6,265	5,978

Notes: For Panel A, each observation is a merger transaction. A large (small) chain is defined as a chain owning more than (less than) 5 nursing homes. A within-market merger happens when the acquirer has affiliates in the same county as the target facility. A cross-market merger happens when the acquirer enters a new market by acquiring a facility outside of its service counties. A low-deficiency chain is defined as a chain with less than six deficiency citations.

Panel B reports means across observations. Each observation is a facility-year combination.

Table 2: DID Results

	-3 to +3				Extended Event Windows			-3 to +3	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Merger	Merger	TWFE	Exit	-3 to +4	-4 to +4	-5 to +5	Divestiture	Chain to Chain
$1[i \in T, t \geq \tau_i]$	-0.530***	-0.545***	-0.491***	-0.545***	-0.669***	-0.616***	-0.719***	0.561	0.345
	(0.183)	(0.187)	(0.170)	(0.187)	(0.199)	(0.204)	(0.208)	(0.463)	(0.256)
Facility Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	Yes	No	No	No	No	No	No
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12490	12097	12097	12097	11307	10894	11496	3021	11155
R^2	0.032	0.034	0.025	0.034	0.036	0.045	0.053	0.089	0.041

Robust standard errors clustered at the facility level are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The following control variables are included in the regressions: nonprofit, government, scu, wage. The following county-level variables are included in the regressions: number of beds in market per 1,000 individuals aged 65+, mean Medicaid, mean Medicare, and mean acuity index across all facilities in market. Column (4) further controls for exit by including an indicator for whether exits occurred in the county in the previous year, in addition to the controls specified above.

Table 3: Patient Selection Outcomes

	(1) Medicaid	(2) Medicare	(3) occupancy	(4) ln(days)	(5) ln(admissions)	(6) acuity	(7) lsdeficiency
$1[i \in T, t \geq \tau_i]$	0.253	0.736**	0.621	0.0105	0.0710***	0.0169	-0.241*
	(0.421)	(0.315)	(0.402)	(0.00772)	(0.0181)	(0.0422)	(0.131)
Facility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	12099	12099	11889	11981	11943	12099	12097
R^2	0.153	0.134	0.034	0.039	0.073	0.242	0.051
Mean	60.37	13.24	85.95	10.40	5.229	11.47	3.601

Robust standard errors clustered at the facility level are reported in parentheses.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The outcome variables in columns (1) - (7) are share of patients supported by Medicaid, share of patients supported by Medicare, facility occupancy rate, log of total patient days, log of total patient admissions, patient acuity index and count of emergency preparedness and fire safety deficiencies.

All these results are estimated using a sample of facilities with a three-year event window.

The following control variables are included in the regressions: nonprofit, government, scu, wage. The following county-level variables are included in the regressions: number of beds in market per 1,000 individuals aged 65+, mean Medicare, mean Medicaid, and mean acuity index across all facilities in market.

Table 4: Quality Effects Decomposition

	-3 to +3		-3 to +4	
	(1) Non-competing	(2) State Medicaid	(3) Non-competing	(4) State Medicaid
Cost Efficiency	-0.601**	-0.549**	-0.754***	-0.788***
	(0.261)	(0.241)	(0.274)	(0.262)
Quality Cost Savings	-0.0469	0.0191	0.00364	0.0376
	(0.198)	(0.191)	(0.224)	(0.213)
Market Power	0.0240	0.0484	0.0811*	0.0789*
	(0.0450)	(0.0371)	(0.0447)	(0.0405)
Overall	-0.624**	-0.481**	-0.670**	-0.671***
	(0.252)	(0.202)	(0.271)	(0.233)
N	11399	11745	10629	10968

Notes: Robust standard errors clustered at the facility level in parentheses. κ_{jt} and n_{jt} are calculated at sample average.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports the decomposition of the marginal effects of nursing home mergers on facility health deficiency citations. The quality cost savings and market power components vary across facilities and are evaluated at sample means. The quality supply equation is reproduced below

$$q_{jt} = \frac{1}{\delta_{nq}}\overline{LOS_{jt}\cdot R_{jt}} - \frac{\delta_{0q}}{\delta_{nq}}\frac{1}{\kappa_{jt}n_{jt}} - \frac{\delta_{qn}}{\delta_{nq}}\frac{1}{\kappa_{jt}} - \frac{\delta_{qw}}{\delta_{nq}}\frac{w_{jt}}{\kappa_{jt}n_{jt}} - \frac{\delta_{qL}}{\delta_{nq}}\frac{\overline{LOS_{jt}}}{\kappa_{jt}n_{jt}}$$
$$- \frac{\delta_{nw}}{\delta_{nq}} w_{jt} - \frac{\delta_{nL}}{\delta_{nq}} \overline{LOS}_{jt} + \frac{\lambda_{np}}{\delta_{nq}}\cdot\frac{1[j = nonprofit]}{\kappa_{jt}n_{jt}} + \frac{\lambda_g}{\delta_{nq}}\cdot\frac{1[j = government]}{\kappa_{jt}n_{jt}}$$
$$- \frac{\delta_{np}}{\delta_{nq}} post_{jt} - \frac{\delta_{qp}}{\delta_{nq}}\frac{1}{\kappa_{jt}n_{jt}}\cdot post_{jt} + \frac{\gamma}{\delta_{nq}}\frac{inmarket_{jt}}{\kappa_{jt}n_{jt}}\cdot post_{jt} - \frac{\delta_{0n}}{\delta_{nq}}$$

Two sets of variables are used to instrument for $\overline{LOS_{jt}}, \overline{R_{jt}}$. Column (1) and (3) report the estimation results using lagged values of non-competing (nc) nursing home characteristics as instruments: $Medicaid_{nc,t-1}$, and $wage_{nc,t-1}$. Non competing nursing homes are selected as facilities that are not in the same county as a focal nursing home and located within a "donut" area 50–100 km away from the focal facility. Column (2) and (4) report the estimation results utilizing differential exposure to state Medicaid reimbursement rates as instruments: $Medicaid_{it-1} \times StateMcaidRate_{st}$ and $Medicaid_{it-1} \times (StateMcaidRate_{st} - StateMcaidRate_{st-1})$.

The overall quality effect of mergers is represented by $-\frac{\delta_{np}}{\delta_n} post_{jt} - \frac{\delta_{qp}}{\delta_{nq}}\frac{1}{\kappa_{jt}n_{jt}} \cdot post_{jt} + \frac{\gamma}{\delta_n}\frac{inmarket_{jt}}{\kappa_{jt}n_{jt}} \cdot post_{jt}$. It can be decomposed into the following three items: $-\frac{\delta_{np}}{\delta_{nq}}$ (Cost Efficiency), $-\frac{\delta_{qp}}{\delta_{nq}\kappa_{jt}n_{jt}}$ (Quality Cost Savings) and $\frac{\gamma}{\delta_{nq}\kappa_{jt}n_{jt}}$ (Market Power).

Table 5: Decomposition - Heterogeneity

	(1) Within	(2) Cross	(3) Large	(4) Small	(5) L. Def	(6) H. Def	(7) H. Staff	(8) L. Staff
Panel A: Event Window -3 to +3								
Cost Efficiency	-0.601**	-0.601**	0.0737	-1.058***	-1.086***	-0.351	-0.461	-0.581*
	(0.261)	(0.261)	(0.419)	(0.322)	(0.322)	(0.542)	(0.358)	(0.334)
Quality Cost Saving	-0.0401	-0.0530	-0.524	0.181	0.00527	-0.0388	-0.387	0.0586
	(0.169)	(0.223)	(0.422)	(0.270)	(0.281)	(0.333)	(0.310)	(0.271)
Market Power	0.164		-0.00814	0.0172	0.0460	-0.0146	0.0807	-0.0224
	(0.307)		(0.192)	(0.0819)	(0.0963)	(0.186)	(0.102)	(0.178)
Overall	-0.477	-0.654***	-0.458	-0.860***	-1.034***	-0.404	-0.767**	-0.542*
	(0.430)	(0.245)	(0.714)	(0.249)	(0.298)	(0.567)	(0.386)	(0.324)
N	11399	11399	8242	8738	8511	8469	8517	8463
Panel B: Event Window -3 to +4								
Cost Efficiency	-0.754***	-0.754***	-0.261	-0.926***	-0.757**	-0.726*	-0.626*	-0.678*
	(0.274)	(0.274)	(0.383)	(0.355)	(0.334)	(0.414)	(0.379)	(0.366)
Quality Cost Saving	0.00313	0.00403	-0.368	0.104	-0.0485	0.0355	-0.0935	-0.0452
	(0.192)	(0.248)	(0.576)	(0.274)	(0.301)	(0.331)	(0.317)	(0.341)
Market Power	0.532*		0.233	0.0744	0.0578	0.266**	0.164	0.0993
	(0.293)		(0.177)	(0.0776)	(0.108)	(0.133)	(0.115)	(0.200)
Overall	-0.220	-0.750***	-0.395	-0.748***	-0.748**	-0.424	-0.555	-0.624*
	(0.412)	(0.271)	(0.586)	(0.252)	(0.337)	(0.402)	(0.380)	(0.371)
N	10629	10629	7647	8184	8019	7812	7895	7936

Robust standard errors clustered at the facility level are reported in parentheses. Significance level:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports the decomposition of the marginal effects of nursing home mergers on facility health deficiency citations. Heterogeneity by within- vs. cross-market mergers uses full-sample parameter estimates, as subsample restriction would preclude identification of the market power effect; marginal effects are evaluated at subsample means. All other heterogeneity analyses (chain size, deficiency level, staffing level) use subsample-specific estimates, with effects evaluated at the corresponding subsample means.

A within-market merger happens when the acquirer has affiliates in the same county as the target facility. A cross-market merger happens when the acquirer enters a new market by acquiring a facility outside of its service counties. A large (small) chain is defined as a chain owning more than (less than) five facilities. Low-deficiency chains are defined as chains with less than six health deficiency citations (sample median). High-staffing chains are defined as chains with more than 3.31 direct care staff hours per resident day (sample median).

Table 6: Staffing and Health Outcomes

Panel A: Staffing Outcomes						
	(1) rn ratio	(2) lpn ratio	(3) cna ratio	(4) dc hours	(5) skn hours	(6) skn hours (pbj)
$1[i \in T, t \geq \tau_i]$	-0.247	0.514**	-0.282	-0.122***	-0.0251**	-0.0260
	(0.189)	(0.257)	(0.280)	(0.0314)	(0.0113)	(0.0171)
Facility Controls	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	11744	11744	11744	11746	11751	4406
R^2	0.067	0.072	0.074	0.134	0.135	0.156
Mean	10.62	22.74	66.77	3.483	1.181	1.202
Panel A: Staffing Outcomes						
	(1) bedsores	(2) contract	(3) restrain	(4) catheter	(5) loss	(6) sum index
$1[i \in T, t \geq \tau_i]$	-0.239	-2.464***	-0.233	-0.170	-0.250	-0.276***
	(0.162)	(0.736)	(0.295)	(0.147)	(0.255)	(0.0873)
Facility Controls	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes
N	12097	12097	11895	12097	12097	11893
R^2	0.024	0.043	0.099	0.021	0.026	0.063
Mean	6.549	27.87	5.228	5.743	8.210	0.0617

Robust standard errors clustered at the facility level are reported in parentheses. Significance level:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Panel A presents estimation results with staffing measures as the dependent variables. Skilled nursing staff comprise registered nurses (RNs) and licensed practical nurses (LPNs), while direct care staff include RNs, LPNs, and certified nursing assistants (CNAs). The outcome variables for columns (1)-(5) are the ratio of RN hours to total direct care nurse hours, the ratio of LPN hours to total direct care nurse hours, the ratio of CNA hours to total direct care nurse hours and direct care nurse hours per resident day. The outcome variable in columns (5)–(6) is skilled nurse hours per resident day. Column (6) restricts the sample to nursing homes for which discrepancies between Payroll Based Journal (PBJ) staffing and CASPER staffing are small.
Panel B reports the the estimation results with health outcomes as dependent variables. The outcome variables in columns (1) - (5) are the share of residents with pressure ulcers (bedsores), contractures (contract), physical restraints (restrain), urethral catheters (catheter), and unplanned weight loss or gain (loss). The summary index in column (6) is defined to be the equally weighted average of z-scores of its components, i.e. outcome variables in the other columns. The z-scores are calculated by subtracting the control group mean and dividing by the control group standard deviation.
The following control variables are included in the regressions: nonprofit, government, scu, wage. The following county-level variables are included in the regressions: number of beds in market per 1,000 individuals aged 65+, mean Medicare, mean Medicaid, and mean acuity index across all facilities in market.
All these results are estimated using a sample of facilities with a three-year event window.

Table 7: Severity of Health Deficiencies: 2009 - 2019

	(1) Total	(2) Low Severity	(3) High Severity
$1[i \in T, t \geq \tau_i]$	-0.592**	-0.544*	0.00500
	(0.291)	(0.286)	(0.0389)
Facility Controls	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes
N	3776	3531	3531
R^2	0.065	0.065	0.028
Mean	5.499	5.322	0.144

Robust standard errors clustered at the facility level are reported in parentheses.

Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table focuses on a subsample of mergers covering years 2009-2019 (consisting of 275 mergers that occurred between 2012 and 2016) where scope and severity information of health deficiencies are available to us.

Column (1) replicates the main difference-in-differences specification using total health deficiencies as the outcome variable. Columns (2) and (3) break down total health deficiencies into two components: low-severity deficiencies, which capture low-severity or administrative categories (tags A–F), and high-severity deficiencies, which correspond to harm-level citations (tags G and above).

All these results are estimated using a sample of facilities with a three-year event window.

Appendix A: Matching

We perform 1-to-1 optimal Mahalanobis matching to select a group of independent facilities that are more similar to the acquired facilities on observed dimensions in year $\tau_i - 1$, i.e. one year before mergers. The distance between nursing homes is computed as the Mahalanobis distance based on the following variables

- variables defined in section 3.4
- the count of health deficiency citations
- the count of any deficiency citations
- number of residents
- direct-care staff hours per resident day[36]
- the ratio of registered nurses divided by registered nurses plus licensed practical nurses

All these variables are lagged by one year. To control the potential quality trend differences between the acquired and control facilities before mergers, we include in matching the lagged difference of the following two continuous variables

- the count of health citations
- the count of any deficiency citations

Also, we require that the control facility selected has the same profit status (for-profit, non-profit, or government) as the acquired facility and is present in the data for all the years that the acquired facility is present. The matching is implemented year by year.

With 1-to-1 optimal Mahalanobis matching, each acquired facility is matched by its closest counterpart. The results of covariate balancing are summarized in Figure A1. Here we show the absolute standardized differences of covariates between the acquired and control facilities in the year $\tau_i - 1$, both for the full control sample (in circle) and the matched control sample (in diamond).[37] Before matching, there are significant differences between the acquired and control facilities in health deficiencies, profit status, government ownership and wage. After matching is implemented, the differences for those covariates are significantly reduced and fall below the 0.1 threshold.[38] Overall, the matching mitigates the confounding effects caused by the differences in observables between acquired and control facilities prior to mergers.

[36]Direct-care staff include registered nurses (RNs), licensed practical nurses (LPNs), and certified nursing assistants (CNAs).

[37]The absolute standardized difference is calculated as the absolute difference in means divided by the standard deviation.

[38]Previous studies suggest that absolute standardized difference less than 0.1 is typically viewed as small differences between groups (Schmitt, 2017).

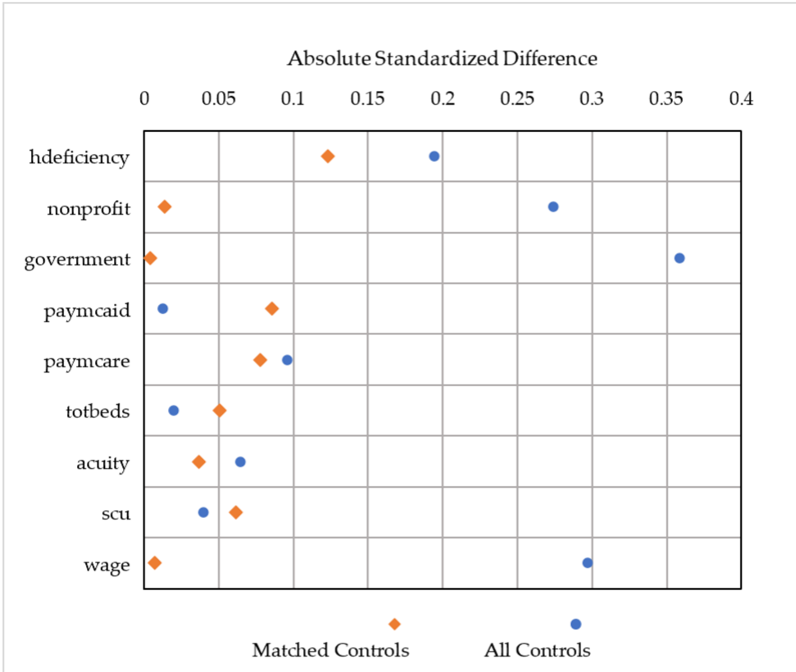
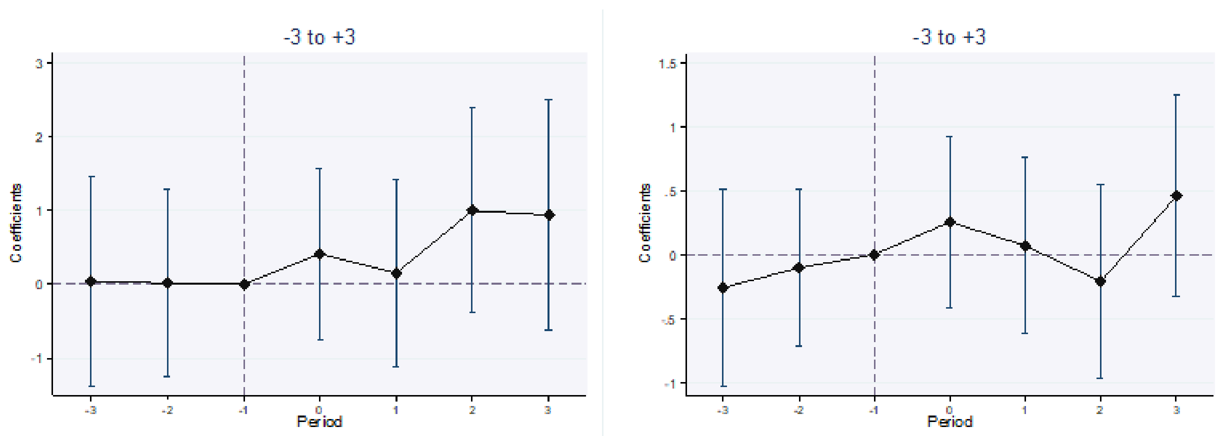


Figure A1: Covariate Balance Before and After Matching

Note: The absolute standardized difference is defined as the absolute difference in means divided by the standard deviation between the acquired and control facilities. The values are computed for the year $\tau_i - 1$.

Appendix B: Supporting Results



(a) Divestiture

(b) Chain-to-Chain

Figure B1: Coefficient Plot of Divestiture/Chain-to-Chain Event Study

Table B1: Event Study Results

	(1) -3 to +3	(2) -3 to +4	(3) -4 to +4	(4) -5 to +5
$1[i \in T, t = \tau_i - 5]$				-0.207
				(0.407)
$1[i \in T, t = \tau_i - 4]$			-0.151	-0.238
			(0.364)	(0.381)
$1[i \in T, t = \tau_i - 3]$	-0.0307	-0.0712	0.0869	0.122
	(0.301)	(0.334)	(0.358)	(0.384)
$1[i \in T, t = \tau_i - 2]$	-0.0543	-0.0867	-0.0618	-0.0347
	(0.267)	(0.284)	(0.311)	(0.337)
$1[i \in T, t = \tau_i]$	-0.452*	-0.488	-0.353	-0.560
	(0.269)	(0.302)	(0.329)	(0.356)
$1[i \in T, t = \tau_i + 1]$	-0.156	-0.308	-0.205	-0.264
	(0.298)	(0.323)	(0.351)	(0.377)
$1[i \in T, t = \tau_i + 2]$	-0.842***	-0.944***	-0.695**	-0.721**
	(0.291)	(0.313)	(0.339)	(0.362)
$1[i \in T, t = \tau_i + 3]$	-0.887***	-0.968***	-0.954**	-0.996**
	(0.314)	(0.340)	(0.371)	(0.390)
$1[i \in T, t = \tau_i + 4]$		-0.980***	-1.090***	-1.168***
		(0.337)	(0.362)	(0.383)
$1[i \in T, t = \tau_i + 5]$				-1.128***
				(0.419)
Facility Controls	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes
N	12097	11307	10894	11496
R^2	0.034	0.037	0.046	0.054
P Value (F Test)	0.980	0.952	0.912	0.882

Robust standard errors clustered at the facility level are reported in parentheses. Significance level:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$
$t = \tau_i$ 1 is the omitted category. The following control variables are included in the regressions: nonprofit, government, scu, wage. The following county-level variables are included in the regressions: number of beds in market per 1,000 individuals aged 65+, mean Medicare, mean Medicaid, and mean acuity index across all facilities in market.
P Value (F test) reports the significance level for testing whether $1[i \in T, t = \tau_i\, k, k > 0]$ are jointly equal to zero.

Table B2: Heterogeneities

	(1) Within	(2) Cross	(3) Large	(4) Small	(5) L. Def	(6) H. Def	(7) H. Staff	(8) L. Staff
Panel A: Event Window -3 to +3								
$1[i \in T, t \geq \tau_i]$	-0.432	-0.601***	-0.267	-0.782***	-0.965***	-0.119	-0.563**	-0.606**
	(0.299)	(0.205)	(0.245)	(0.223)	(0.205)	(0.258)	(0.227)	(0.249)
Facility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7755	10375	8824	9306	9077	9053	9081	9049
R^2	0.042	0.037	0.039	0.040	0.040	0.042	0.042	0.039
Panel B: Event Window -3 to +4								
$1[i \in T, t \geq \tau_i]$	-0.399	-0.810***	-0.496*	-0.818***	-0.856***	-0.459	-0.670***	-0.693***
	(0.320)	(0.217)	(0.261)	(0.241)	(0.216)	(0.284)	(0.243)	(0.267)
Facility Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County Level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Cohort FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Specific Time Trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	7321	9627	8221	8727	8568	8380	8449	8499
R^2	0.043	0.041	0.041	0.040	0.042	0.044	0.043	0.041

Robust standard errors clustered at the facility level are reported in parentheses. Significance level:
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The following control variables are included in the regressions: nonprofit, government, scu, wage. The following county-level variables are included in the regressions: number of beds in market per 1,000 individuals aged 65+, mean Medicare, mean Medicaid, and mean acuity index across all facilities in market.

A within-market merger happens when the acquirer has affiliates in the same county as the target facility. A cross-market merger happens when the acquirer enters a new market by acquiring a facility outside of its service counties. A large (small) chain is defined as a chain owning more than (less than) five facilities. Low-deficiency chains are defined as chains with less than six health deficiency citations (sample median). High-staffing chains are defined as chains with more than 3.31 direct care staff hours per resident day (sample median).

Table B3: Decomposition: High vs. Low HHI

	-3 to +3			-3 to +4		
	(1)	(2)	(3)	(4)	(5)	(6)
	High HHI	Low HHI	Cross	High HHI	Low HHI	Cross
Cost Efficiency	-0.582**	-0.582**	-0.582**	-0.759***	-0.759***	-0.759***
	(0.256)	(0.256)	(0.256)	(0.273)	(0.273)	(0.273)
Quality Cost Saving	-0.0761	-0.0457	-0.0688	0.00823	0.00475	0.00708
	(0.253)	(0.152)	(0.229)	(0.296)	(0.171)	(0.255)
Market Power	0.0856	0.0513		0.826	0.477	
	(0.623)	(0.373)		(0.595)	(0.343)	
Market Power X High HHI	0.334			-0.0591		
	(0.653)			(0.660)		
Overall	-0.238	-0.576	-0.650***	0.0161	-0.277	-0.752***
	(0.530)	(0.486)	(0.243)	(0.578)	(0.447)	(0.269)
N	11399	11399	11399	10629	10629	10629

Notes: Robust standard errors clustered at the facility level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

This table reports the marginal effects of nursing home mergers on facility-level health deficiency citations, decomposed into three components: cost efficiency, quality cost savings, and market power. The quality cost savings and market power components vary across facilities and are evaluated at subsample means.
This table tests a specification where $\gamma = \gamma_1 + \gamma_2$ *HighHHI* where *HighHHI* = 1 for markets with *HHI* > 1500. Lagged values of non-competing nursing home characteristics are used as instruments for LOS_{jt}, R_{jt} . The quality supply equation is reproduced below

$$q_{jt} = \frac{1}{\delta_{nq}} LOS_{jt} \cdot R_{jt} - \frac{\delta_{0q}}{\delta_{nq}} \frac{1}{\kappa_{jt} n_{jt}} - \frac{\delta_{qn}}{\delta_{nq}} \frac{1}{\kappa_{jt}} - \frac{\delta_{qw}}{\delta_{nq}} \frac{w_{jt}}{\kappa_{jt} n_{jt}} - \frac{\delta_{qL}}{\delta_{nq}} \frac{LOS_{jt}}{\kappa_{jt} n_{jt}} - \frac{\delta_{nw}}{\delta_{nq}} w_{jt} - \frac{\delta_{nL}}{\delta_{nq}} LOS_{jt}$$
$$+ \frac{\lambda_{np}}{\delta_{nq}} \cdot \frac{1[j = nonprofit]}{\kappa_{jt} n_{jt}} + \frac{\lambda_g}{\delta_{nq}} \cdot \frac{1[j = government]}{\kappa_{jt} n_{jt}}$$
$$- \frac{\delta_{np}}{\delta_n} post_j - \frac{\delta_{qp}}{\delta_{nq}} \frac{1}{\kappa_{jt} n_{jt}} \cdot post_j + \frac{\gamma_1 + \gamma_2 \cdot HighHHI}{\delta_n} \frac{Within_{jt}}{\kappa_{jt} n_{jt}} \cdot post_j - \frac{\delta_{0n}}{\delta_n} + _j$$

Appendix C: Demand Model

The demand model is based on seniors' choice of nursing homes for long-term care. We assume that a senior i decides between an outside good ($j = 0$) and nursing homes ($j = 1, 2, ..., J_m$) in her residing county m to maximize her utility. Examples of the outside good include long-term care delivered to the senior's home by informal caregivers (family members, relatives, or friends) or formal care by home care agencies. Individual i's utility from facility j in year t is defined as

$$U_{ijt} = \delta_{jt} + v_{ijt} \tag{4}$$

where the mean utility δ_{jt} is specified as follows

$$\delta_{jt} = X_{jt}\beta + aq_{jt} + \lambda_m + \lambda_t + \xi_{jt}$$

The q_{jt} is the quality of care for facility j measured by the number of health deficiency citations. X_{jt} denotes a vector of facility characteristics affecting the mean utility, λ_m (λ_t) represents county (year) specific fixed effects, ξ_{jt} denotes unobserved facility characteristics. Following Berry (1994),

$$v_{ijt} = \zeta_{igt} + (1-\sigma)\varepsilon_{ijt} \tag{5}$$

follows an i.i.d. extreme value distribution which generates a nested logit structure (see equation (8) below). The advantage of a nested logit structure is that it allows for closer substitution within a nest. We assume that all facilities are placed in a single nest but they are separated from the outside good (placed in another nest). $0 < \sigma < 1$ measures the correlation among choices within the nursing home nest. A higher σ implies higher homogeneity within the nursing home nest, i.e. choices within the nursing home nest are closer substitutes for a nursing home than the outside good.

Note that price is omitted in the mean utility function for the following reasons. Price competition is limited in the nursing home industry as the majority of the nursing home revenues come from Medicare and Medicaid enrollees whose nursing home stays are paid by federal or state governments. In our sample, 60% of the residents are covered by Medicaid, and 13% are covered by Medicare. Payments for these residents are competition at state or federal levels.

Aggregating the nursing home choices across consumers, the market share of facility j is given by the within-group shares ($s_{jt|gt}$, the share of residents in facility j out of all residents in nursing homes within county m) multiplied by the group share (s_{gt}, the total number of nursing home residents in county m divided by total number of seniors in county m):

$$s_{jt} = s_{jt|gt} \cdot s_{gt} \tag{6}$$

$$= \frac{e^{\delta_{jt}/(1-\sigma)}}{V_{mt}^{\sigma}(1 + V_{mt}^{1-\sigma})} \tag{7}$$

where $V_{mt} = \sum_{k\in J} e^{\delta_{ji}/(1-\sigma)}$.

Therefore, demand for facility j can be written as $M_{mt} \cdot s_{jt}$ where M_{mt} equals the total number of seniors in county m.

Assuming the mean utility from the outside good to be 0, with equation (7), the following expression holds.

$$\ln(S_{jt}/S_{0t}) = X_{jt}\beta + aq_{jt} + \sigma\ln(S_{jt|gt}) + \lambda_m + \lambda_t + \xi_{jt} \tag{8}$$

Since our demand model only requires facility-level characteristics as explanatory variables, we only utilize information from CASPER dataset for the demand estimation analysis.

C.1 Instruments

The unobserved facility characteristics ξ_{jt} are likely to be correlated with both quality and within group share. To address this endogeneity concern, we employ an instrumental variables approach following Berry (1994). We use observable and exogenous product characteristics of facilities' local competitors to instrument for quality and within-group share. Here the instruments are the number of beds and the share of Medicare residents of local competitors. These variables do not affect consumers' demand decisions directly. However, they affect the rival's costs, staffing, and quality choice and thereby have an indirect effect on the quality choice of a nursing home when it competes with other facilities.

There is a caveat for using our instruments. In the nursing home market, capacity constraints are often binding. When a competitor is full, patients are mechanically forced to the focal facility due to rationing, regardless of their preference for quality. Competitor bed capacity may correlate with the focal firm's demand shocks, violating the exclusion restriction. Because rationing induces co-movement in observed market shares and quality across facilities within the same nest, it affects the substitution patterns in the nested logit model and leads to an upward bias in the substitution parameter σ.

C.2 Demand Estimates

Table C1 reports the results of demand estimation using 2SLS. The F-statistics on the instruments is 82.52, suggesting a rejection of weak instruments. All the coefficients are significant and have expected signs. Demand rises in correlation with the percentage of Medicaid residents, the number of beds, the presence of a special care unit, and nursing homes' capability of taking care of sicker residents (measured by residents' acuity index). Further, consumers value chain ownership, while showing less preference for nonprofit, government or hospital-based facilities.

The coefficient of $hdeficiency$ is negative and significant. A higher number of health deficiency citations decreases demand, i.e. consumers value quality of care when selecting nursing homes for long-term care and support services. The average own elasticity with respect to the number of health deficiency citations is -0.27. The interpretation is that when the number of deficiency citations increases by 1 (or around 10% of the full sample mean of $hdeficiency$), market share decreases by 2.7 percent. Further, the coefficient of the within-group share is 0.693, and significant. It implies a closer substitution among nursing homes than between a nursing home and the outside good.

Table C1: Demand Estimation

	(1) lnshareratio
hdeficiency	-0.0152***
	(0.00264)
lshare_g	0.693***
	(0.0101)
nprofit	-0.00996***
	(0.00273)
government	-0.0343***
	(0.00334)
chain_own	0.0137***
	(0.000947)
hospbase	-0.132***
	(0.00444)
Medicaid	0.00185***
	(0.0000753)
Medicare	-0.000266***
	(0.0000598)
totbeds	0.00242***
	(0.0000623)
acuity	0.00407***
	(0.000357)
scu	0.0281***
	(0.00124)
N	327852
R^2	0.920

Robust standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: Model is estimated using the 2SLS method with the number of beds and share of Medicare residents of local competitors as instruments.