Spillover Effects of Nursing Home Closures on Resident Health in Neighboring Facilities: Evidence from Different Market Structures

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Abstract

I study how nursing home closures affect the health of residents who remain in surviving facilities. Using resident-level Minimum Data Set (MDS 3.0) assessments linked to facility and county characteristics from 2011–2017, I apply a staggered difference-in-differences design with propensity-score matching to estimate the causal impact of nearby closures. The results show substantial heterogeneity across market structures. In concentrated markets, closures increase occupancy, reduce registered-nurse staffing, and raise the prevalence of chronic and neurodegenerative conditions such as heart failure, Alzheimer's disease, and chronic respiratory illness. In contrast, in competitive markets, closures are mostly absorbed without noticeable decline and often lead to slight improvements in health outcomes. The heterogeneity also extends across facility types. For example, nonprofit, chain-affiliated, and low-Medicaid share facilities are more resilient to closures than for-profit, independent, and high-Medicaid share nursing homes. These findings demonstrate that the effects of provider exit depend critically on local capacity, competition, and institutional characteristics. The underlying mechanism is consistent with these patterns: closures raise occupancy and reduce staffing per resident, particularly in concentrated markets, where surviving facilities face tighter capacity and labor constraints. In conclusion, the evidence indicates that competition enhances allocative efficiency when capacity is elastic, whereas closures in concentrated markets tighten resource constraints and diminish the quality of care. Policy responses should therefore be market-sensitive–raising Medicaid reimbursement in low-margin areas and relaxing certificate-of-need (CON) restrictions–to preserve access and quality in vulnerable regions.

Keywords: Nursing Home Closures; Market Structure; Capacity Strain; Quality of Care

JEL Codes: I11, I14, I18, J14, H75

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1 Introduction

The long-term care sector is undergoing major demographic and policy changes. As the baby-boomer generation ages, demand for institutional care has risen, adding financial pressure on federal and state programs. Policymakers have responded by expanding home- and community-based services (HCBS) as a lower-cost alternative to nursing homes (Castle et al., 2009; Tyler & Fennell, 2017), contributing to a steady contraction in nursing home capacity (Flinn, 2020; Sharma et al., 2021). Yet closures do not eliminate the need for institutional care. Recent evidence shows that 84.6 percent of residents from closing facilities move to another nursing home (Olenski, 2023), indicating that HCBS supplements–but does not replace–facility-based services. These trends raise an important question: when a nursing home closes, what happens to residents who remain in nearby facilities, and how do these effects differ across local market structures?

A closure constitutes a sudden market shock. Surviving facilities must absorb displaced residents, leading to higher occupancy and increased strain on staffing capacity (Bowblis & Vassallo, 2014; Olenski, 2023; Xu et al., 2025). At the same time, the loss of competitors alters market power and changes incentives for quality. In the Bowblis and Vassallo framework, such exits can generate either efficiency gains or welfare losses. When closures remove inefficient or low-quality providers, remaining facilities may respond by improving management and raising care standards. Conversely, if closures reduce competition and exacerbate operational strain, they may lead to overcrowding, staff fatigue, and declines in quality (Bowblis & Vassallo, 2014). The overall impact therefore depends critically on local market structure–an aspect that prior research has seldom examined in detail.

Much less is known about the post-closure period, particularly for residents who remain in surviving facilities. A substantial literature has examined the determinants of nursing home closures, focusing on ownership, Medicaid reimbursement, and competition (Castle et al., 2009; Harrington et al., 2011; Lin, 2015). Notable exceptions include Bowblis and Vassallo (2014), who find that average quality improved following rural closures, and Xu et al. (2025), who show that rural closures increased occupancy without harming financial performance. These studies suggest that consolidation can enhance efficiency through economies of scale or selection. However, they share key limitations: they typically do not distinguish between displaced and incumbent residents,

rely on regulatory or staffing measures rather than clinical outcomes, and treat rural markets as homogeneous. As a result, the welfare implications of closures for incumbent residents remain uncertain.

This paper provides new causal evidence on how nursing home closures affect the health of residents who remain in surviving facilities and how these effects vary across market structures. I assemble a resident-level panel that links Minimum Data Set (MDS) assessments with facility and county characteristics from the Centers for Medicare & Medicaid Services (CMS) and other administrative sources. The empirical strategy combines a staggered difference-in-differences design with propensity score matching to address the non-random timing and location of closures (Callaway & Sant'Anna, 2021; Stuart, 2010). I compare changes in resident outcomes between facilities in counties that experience a closure and those in matched counties without one, conditioning on resident and facility characteristics.

A key advantage of the data is the ability to track residents across facilities and exclude those who relocate following a closure. This design isolates spillover effects on incumbents rather than direct effects on displaced individuals. I examine a comprehensive set of health outcomes–including mortality, hospitalization, and active diagnoses–that capture direct clinical manifestations of resident well-being. Unlike prior studies that rely on regulatory compliance or staffing ratios as proxies for quality, these measures reflect physician-documented health conditions from standardized clinical assessments. This approach provides a clinically grounded, resident-centered view of care quality, allowing for the detection of subtle yet meaningful shifts in health status that aggregate indicators often obscure.

The analysis yields three main findings. First, the effects of closures vary sharply by market structure. In concentrated markets, closures raise occupancy, reduce registered nurse (RN) staffing, and worsen chronic and neurodegenerative conditions such as heart failure, Alzheimer's disease, and chronic respiratory illness by on the order of 3–10 percent relative to their baseline prevalence. In competitive markets, by contrast, closures are absorbed without deterioration and are sometimes accompanied by modest quality improvements. This heterogeneity highlights that the consequences of provider exit depend critically on local capacity and competition. Second, facility characteristics further shape how nursing homes adjust to closure shocks. Nonprofit, chain-affiliated, and financially stronger (low-Medicaid share) facilities show greater resilience, typically maintaining or

improving resident outcomes by a few percentage points relative to baseline, while for-profit, independent, and high-Medicaid share nursing homes–often operating with tighter budgets and limited staffing flexibility–are more vulnerable to quality deterioration of similar magnitude. These differences underscore that the ability to absorb market disruptions depends not only on competition and capacity at the market level but also on organizational and financial resources at the facility level. Third, mechanism analyses indicate that these market-dependent effects operate primarily through changes in capacity and staffing. Following a closure, surviving facilities experience higher occupancy–on the order of 1–2 percent of pre-closure means–and a compositional shift away from RNs toward licensed practical nurses (LPNs), with RN hours per resident day falling by roughly 2–5 percent in less competitive markets where limited capacity amplifies strain.

This paper makes three primary contributions. First, it advances the literature on nursing home market dynamics by demonstrating that closure effects are heterogeneous across both markets and facilities. Prior studies generally portray consolidation as efficiency-enhancing through competition or economies of scale (Bowblis & Vassallo, 2014; Olenski, 2023; Rahman et al., 2013). My findings confirm this mechanism in competitive markets but reveal the opposite in concentrated ones. Moreover, nonprofit, chain-affiliated, and low-Medicaid share facilities remain more resilient than for-profit, independent, and high-Medicaid share nursing homes, underscoring that both market competition and facility capacity shape the consequences of provider exit. Second, the analysis isolates the causal effects of closures on incumbent residents by excluding displaced residents who relocate following a closure. Prior work typically pools incumbents and displaced individuals, conflating short-term deterioration with long-term recovery. Because displaced residents often experience initial declines followed by gradual improvement (Olenski, 2023), pooling them biases estimates–understating short-term harm or overstating long-term benefits. Restricting the sample to incumbents thus yields cleaner identification of spillover effects and a more policy-relevant measure of how closures reshape the care environment. Third, the paper extends quality measurement beyond regulatory or staffing proxies by using resident-level active diagnosis data from the MDS to capture direct health outcomes. This clinically grounded approach links facility-level shocks to specific dimensions of resident health, uncovering mechanisms of improvement and deterioration that are invisible in staffing-based metrics.

From a policy perspective, these findings underscore the importance of market-sensitive reg-

ulation and planning in the long-term Care sector. Medicaid's ongoing "rebalancing" toward home- and community-based services (HCBS) has expanded consumer choice and reduced institutional expenditures, but the resulting contraction of nursing home capacity has had uneven effects across markets. In competitive or urban areas, closures may enhance efficiency by reallocating resources toward higher-quality providers. Policy efforts in such contexts should focus on facilitating smooth transitions and maintaining quality standards during consolidation. In contrast, in capacity-constrained markets, the loss of even a single facility can destabilize the local care network, exacerbate staffing shortages, and leave vulnerable residents with few alternatives. Targeted responses are therefore needed to preserve access and quality in these settings. Policymakers could raise Medicaid reimbursement rates in high-need or low-margin regions, provide temporary financial or staffing support to surviving facilities, and encourage new entry or expansion to restore capacity. Relaxing certificate-of-need (CON) restrictions in underserved areas could also stimulate investment and maintain geographic coverage (Park & Werner, 2011; Rahman et al., 2016). More broadly, an effective regulatory strategy should not seek to prevent closures outright, but to ensure that local markets have the flexibility and resources to absorb them without compromising resident welfare.

The remainder of the paper proceeds as follows. Section 2 reviews institutional background and related literature. Section 3 describes the data sources, sample construction, and key variables. Section 4 outlines the empirical strategy, including the staggered difference-in-differences design and matching procedure. Section 5 presents the main findings and mechanism analyses, and Section 6 concludes with policy implications and directions for future research.

2 Background

2.1 Reblancing Long-Term Care in the U.S.

Medicaid has long been the primary payer of long-term services and supports (LTSS) in the United States, and its original design was heavily oriented toward institutional care. Under federal law, states are required to provide nursing facility services as a mandatory Medicaid benefit for eligible beneficiaries, while home- and community-based services (HCBS) have historically been optional. As a result, the early Medicaid LTSS system developed around nursing homes as the

default mode of care (Congressional Research Service, 2024; Medicaid and CHIP Payment and Access Commission (MACPAC), 2023b).

Beginning in the 1980s, concerns over rising institutional costs and shifting consumer preferences for independence led to a gradual policy shift—commonly referred to as the "rebalancing" of long-term care (Keenan, 2010). A pivotal moment came with the Omnibus Budget Reconciliation Act of 1981, which introduced Section 1915(c) of the Social Security Act, allowing states to use Medicaid waivers to fund HCBS as an alternative to institutional care (Kitchener et al., 2004; LeBlanc et al., 2000; U.S. Congress, 1981). This reform represented the first significant federal initiative allowing states to create community-based alternatives.

In the following decades, major federal actions reinforced this transition. The Americans with Disabilities Act of 1990 and the Supreme Court's decision in Olmstead v. L.C. (1999) established a legal foundation for reducing unnecessary institutionalization (Americans with Disabilities Act (ADA), 1990; U.S. Supreme Court, 1999). Subsequent federal initiatives—such as the Deficit Reduction Act of 2005, the Money Follows the Person Demonstration, and key provisions of the Affordable Care Act of 2010—provided financial incentives and programmatic flexibility for states to expand HCBS capacity and rebalance Medicaid spending (Hargan, 2017; E. A. Miller & Nadash, 2014).

Consequently, these reforms fundamentally altered the structure of Medicaid long-term care. In 1988, approximately 10 percent of LTSS spending was allocated to HCBS, but this share steadily increased over time. By around 2013, spending on HCBS surpassed institutional LTSS for the first time, and the gap has continued to widen. By 2020, HCBS accounted for approximately 62 percent of Medicaid LTSS expenditures, increasing to 64.6 percent by 2022 (Chidambaram & Burns, 2024; Congressional Research Service, 2024). In the same year, roughly 86 percent of LTSS users received HCBS rather than institutional care (Murray et al., 2024; Wysocki et al., 2024). This sustained shift in public spending reflects both fiscal and normative priorities—containing costs while aligning service delivery with individual preferences for community-based living.

The rebalancing of Medicaid long-term care has also reshaped the market environment for institutional providers. As policy emphasis and funding increasingly favored community-based alternatives, many nursing facilities faced declining demand, tighter reimbursement, and growing competition from non-institutional care models (Coburn et al., 2016; Konetzka, 2014; Tyler &

Fennell, 2017).

2.2 The Trend of Nursing Home Closure

Over the past two decades, the United States has experienced a persistent contraction in the nursing home sector. The number of operating facilities has declined since the early 2000s, with the pace of closures rising notably on the eve of the pandemic (e.g., 118 per year in 2011–2017, 143 in 2018, and 200 in 2019) (Flinn, 2020; K. E. Miller et al., 2023; Sharma et al., 2021).

A combination of economic, demographic, and policy factors underlies this trend (Castle et al., 2009; Harrington et al., 2011). Rising operating costs—particularly for labor, regulatory compliance, and infection control—have eroded already thin margins, and persistent staffing shortages have increased wage pressures and reduced operational flexibility (Bowblis et al., 2024; Centers for Medicare & Medicaid Services, 2023; Muench et al., 2021). At the same time, Medicaid reimbursement rates have frequently lagged actual costs: federal analyses indicate that in 2019, Medicaid base payments covered a median of roughly 84–86 percent of reported nursing home costs, with many facilities below that level (Medicaid and CHIP Payment and Access Commission (MACPAC), 2023a; E. Miller et al., 2024). For example, if a facility incurs $100 in daily care costs for a Medicaid resident, expected reimbursement would average about $84–$86, leaving the facility to absorb or offset the shortfall through other revenues, supplemental payments, or cross-subsidization from private-pay residents. Demographic and policy shifts have also weakened institutional demand, as the continued expansion of home- and community-based services (HCBS) has diverted lower-acuity individuals toward community settings (Murray et al., 2024).

The COVID-19 pandemic sharply intensified these preexisting challenges. Nursing homes faced acute staffing disruptions, added infection-control expenditures, and steep occupancy declines during the public health emergency (Hughes, Feng, et al., 2023; Hughes, Segelman, et al., 2023; Orewa et al., 2024). Since 2020, at least 700 nursing homes have permanently closed nationwide, displacing more than 28,000 residents and increasing pressure on remaining facilities to absorb the relocated individuals (American Health Care Association (AHCA), 2024; Skilled Nursing News, 2024). These closures have generated local market disruptions with potential implications for the quality, stability, and continuity of care among surviving nursing homes.

Closures have not occurred randomly. They have been concentrated in economically and opera-

tionally vulnerable markets: facilities with small scale, low occupancy, heavier reliance on Medicaid, or tight labor markets are disproportionately at risk (Castle et al., 2009). Rural areas have faced especially severe pressures. Rural nursing homes tend to operate on a smaller scale, serve lower-income populations, and depend heavily on Medicaid revenue, leaving them more vulnerable to fluctuations in demand and rising labor costs (National Rural Health Association, 2024). Although the absolute number of closures is higher in metropolitan counties (reflecting a larger facility base), the number of counties experiencing at least one closure has been greater in non-metropolitan regions. The closure rate has been higher: between 2008 and 2018, approximately 400 non-metropolitan counties recorded at least one closure, compared to 368 metropolitan counties, with closure rates of 10.4% and 7.2%, respectively (Sharma et al., 2021). These patterns highlight the structural fragility of rural long-term care markets even before the COVID-19 pandemic.

Overall, the accelerating pace of closures underscores widening disparities in the geography of institutional care. While some capacity reduction aligns with rebalancing toward HCBS, the uneven distribution of closures across vulnerable and rural markets raises broader questions about access, competition, and systemic resilience. Understanding these closure dynamics and their spillover effects on nearby facilities is crucial for assessing the long-term consequences of structural change in the nursing home industry.

2.3 Mechanisms Linking Closures to Outcomes at Neighboring Facilities

When a nursing home closes, nearby facilities must absorb displaced residents, adjust staffing, and respond strategically to the new market environment. Whether these adjustments lead to higher or lower quality is theoretically ambiguous. Following the framework proposed by Bowblis and Vassallo (2014), the net effect of a closure depends on how the exit alters both the demand faced by surviving facilities and their incentives to invest in quality.

In the Bowblis and Vassallo model, each facility i chooses a level of quality q_i to maximize profit:

$$\pi_i = P(Q_i, Q_{-i}) \cdot D_i(Q_i, Q_{-i}) - C(Q_i),$$

where $P(\cdot)$ represents the effective price (or per-resident revenue) that depends on overall market quality Q_{-i}, $D_i(\cdot)$ is the facility's demand, and $C(\cdot)$ is the cost of providing quality. The first-order

condition with respect to quality can be expressed as:

$$\frac{\partial \pi_i}{\partial Q_i} = \frac{\partial P}{\partial Q_i} D_i + P \frac{\partial D_i}{\partial Q_i} - C'(Q_i) = 0.$$

This formulation shows that the marginal incentive to invest in quality depends on two terms: (1) how sensitive demand is to quality ($\frac{\partial D_i}{\partial Q_i}$), and (2) how competition shapes the relationship between price and quality ($\frac{\partial P}{\partial Q_i}$) (Grabowski & Hirth, 2003; Starkey et al., 2005; Zinn, 1994).

When a competitor exits, the market environment shifts in two opposing ways:

(1) **Demand expansion and scale economies.** A closure transfers some residents from the current facility to survivors, effectively increasing their potential demand. If higher occupancy improves financial viability or allows cost spreading across a larger census, the marginal benefit of quality ($\frac{\partial D_i}{\partial Q_i}$) may rise. In this case, closures can lead to quality improvements through a "competitive reallocation" or scale effect.

(2) **Reduced competitive pressure.** However, the loss of a competitor also weakens incentives to maintain quality as a means of attracting residents. If demand becomes less elastic with respect to quality (that is, $\frac{\partial D_i}{\partial Q_i}$ falls) or if facilities face less risk of losing residents to rivals, they may reduce costly quality investments. This "monopoly effect" pushes quality downward.

The direction of the net effect depends on which force dominates. If economies of scale and positive demand shifts are strong, quality may increase after closure. Conversely, if the market becomes more concentrated and demand is less responsive, quality may deteriorate. Bowblis and Vassallo demonstrate that, under reasonable parameterizations, both outcomes are theoretically possible: closure can raise or lower quality depending on cost curvature, demand elasticity, and the pre-closure level of competition (Bowblis, 2012; Bowblis & Vassallo, 2014; Starkey et al., 2005).

Formally, comparative statics from their model imply that:

$$\frac{\partial Q_i^*}{\partial N} < 0 \quad \text{if competition dominates,} \qquad \frac{\partial Q_i^*}{\partial N} > 0 \quad \text{if scale effects dominate,}$$

where N denotes the number of competitors. Thus, a reduction in N (closure) can either increase or decrease equilibrium quality Q_i^*, conditional on market structure and financial constraints.

In rural markets, where facilities are few and often capacity-constrained, closures may tighten labor and occupancy pressures, leading to quality declines (Lin, 2015; Spilsbury et al., 2011). In more competitive or urban markets, closures might instead eliminate low-quality competitors, enhancing the financial efficiency of survivors and improving the average quality. Hence, the theoretical prediction is fundamentally heterogeneous—closure shocks can generate upward or downward spillovers depending on local market characteristics. This ambiguity motivates the empirical analysis in the following sections, which examines how neighboring facilities respond to closure shocks in practice.

3 Data

3.1 Sources

This study combines several complementary datasets to identify nursing home closures, measure resident outcomes, and construct facility- and county-level characteristics. Each dataset serves a distinct role—tracking facility operations, capturing resident health assessments, describing organizational and staffing structures, and situating facilities within their local demographic and economic context. Table A1 summarizes the primary data sources, their spatial units, temporal coverage, and reporting frequency used in the analysis.

To identify nursing home entries and exits, I use the Medicare Provider of Services (POS) file, 1Q 2025 release. The POS is a comprehensive registry of all Medicare-certified providers maintained by the Centers for Medicare & Medicaid Services (CMS). It includes each facility's provider number, original participation date, termination code, and termination or expiration date, which together allow identification of opening and closure events for Skilled Nursing Facilities (SNFs) and Nursing Facilities (NFs). By comparing successive quarterly files, I verify operational continuity and distinguish permanent closures from temporary suspensions or ownership changes.

Resident health outcomes are measured using the Minimum Data Set (MDS) 3.0, a federally mandated clinical assessment of all residents in Medicare- or Medicaid-certified nursing homes. The MDS is collected at admission, quarterly, annually, and upon significant change in condition, providing a longitudinal and standardized view of resident status. It contains detailed indicators of demographics, cognitive performance, behavior and functional status, health and skin conditions, medication use, and active diagnoses (Hawes et al., 1997).

Facility-level characteristics come from Long-Term Care: Facts on Care in the U.S. (LTCFocus), curated by Brown University's Center for Gerontology and Healthcare Research. LTCFocus integrates CMS administrative data, OSCAR/CASPER, PECOS, and MDS-based aggregates to describe facility structure, staffing, and case mix. Key variables include occupancy rate, certified beds, ownership type (for-profit vs. nonprofit), chain affiliation, hospital-based status, and resident demographics. Financial and operational indicators include payer mix, acuity index, and staffing intensity measured as certified nursing assistant (CNA), licensed practical nurse (LPN), and registered nurse (RN) hours per resident day (HPRD). These measures enable analysis of how financial composition and staffing resources relate to closure risk and resident outcomes.

To capture local socioeconomic and health system characteristics, I incorporate county-level data from the Area Health Resource File (AHRF), maintained by the Health Resources and Services Administration (HRSA). The AHRF provides demographic, economic, and health system indicators, including population size, the share of the population aged 65 and older, racial composition, median household income, and dual-eligibility rates for Medicare and Medicaid. These variables characterize the broader market and socioeconomic environment in which each facility operates.

Data integration proceeds in two steps. First, I merge MDS with facility-level datasets (POS and LTCFocus) using the CMS Certification Number (CCN) to ensure consistent identification across sources and years. Second, I append county-level characteristics from the AHRF using Federal Information Processing Standard (FIPS) codes. The resulting panel combines operational, structural, and resident-level information with local demographic and economic context.

3.2 Sample

The analytic period for this study spans 2011–2017. I began in 2011 because the Minimum Data Set (MDS) 3.0 was first implemented nationally in October 2010, making 2011 the first full calendar year of consistent coverage and standardized resident assessments across U.S. nursing homes (Hawes et al., 1997). The endpoint of 2017 is chosen because the key staffing variables—certified nursing assistant (CNA), licensed practical nurse (LPN), and registered nurse (RN) hours per resident day (HPRD)—were redefined in 2018 when CMS transitioned from OSCAR/CASPER data to Payroll-Based Journal (PBJ) reporting (Harrington et al., 2020). Restricting the sample

to this window ensures temporal consistency in both resident- and facility-level measures.

The sample is limited to facilities located in the 48 contiguous states and the District of Columbia, excluding Alaska and Hawaii. These two states exhibit unique geographic isolation, workforce structures, and healthcare delivery systems that render them less comparable to the broader U.S. nursing home market.

To define the study population, I restrict the analytic sample to facilities that are dually certified as both Skilled Nursing Facilities (SNFs) and Nursing Facilities (NFs) under Medicare and Medicaid. Facilities certified only as SNFs primarily provide short-stay post-acute rehabilitation care and thus do not align with the long-term custodial care population that is the focus of this study. Conversely, NF-only facilities are relatively rare, operate at a smaller scale, and are disproportionately located in rural areas. Restricting the sample to dually certified facilities enhances comparability across institutions and follows standard practice in the literature on long-term care markets and closures (e.g., Bowblis & Vassallo, 2014).

The initial sample comprises 13,807 unique nursing homes, observed annually from 2011 to 2017, resulting in 96,649 facility-year observations. I exclude facilities with missing information on dependent variables—including occupancy rate, staffing levels (CNA, LPN, and RN HPRD), and resident health outcomes derived from the MDS—to ensure the reliability and consistency of estimates.

I further exclude 1,729 incumbent facilities that were exposed to a closure in 2011, as these lack a pre-treatment period necessary for identifying changes relative to closure exposure. For regression analyses, each treated facility contributes observations from three years before and two years after a closure event, consistent with standard event-study frameworks. I also exclude monopoly markets (counties with only one operating nursing home) because these markets cannot experience competition effects from neighboring closures.

The final analytic sample comprises 84,546 facility-year observations from 12,078 unique nursing homes across 48 states and the District of Columbia over 2011–2017. This balanced panel provides a comprehensive view of nursing home operations, staffing patterns, resident outcomes, and local market characteristics within the evolving landscape of long-term care closures in the United States.

3.3 Variables

3.3.1 Independent Variable

The key independent variable in this study is the closure of a nursing home within a given market. I define a facility as closed if its termination status in the Medicare Provider of Services (POS) file indicates either a voluntary or involuntary termination. However, the POS alone does not perfectly distinguish actual closures from administrative or certification changes. For example, a facility may appear as terminated but subsequently reopen under a new Provider ID at the same address, continue operations as a Medicaid-only Nursing Facility (NF) after losing its Skilled Nursing Facility (SNF) certification, or transition to dual accreditation under a new CMS Certification Number (CCN).

To improve measurement accuracy, I implement a multi-step validation procedure following approaches used in prior research (e.g., Lin, 2015). First, I verify whether each terminated facility disappears from both the LTCFocus and Nursing Home Compare datasets in the subsequent year. If the facility remains listed, I further check for persistence of resident-level records in the Minimum Data Set (MDS) 3.0. Second, I utilize a large language model (ChatGPT 5) to aid in identifying potential cases of nominal closures—that is, facilities that have changed their CCN but continue to operate at the exact location. Using facility-level information, including facility name, address, phone number, ZIP code, and entry and exit date, the model flagged candidate pairs that likely represent the same physical site under different identifiers. I then manually verified these cases and excluded 99 facilities that were found to have continued operations despite apparent termination, ensuring that the closure variable captures genuine facility exits rather than administrative reclassification.

A key step in defining exposure to closure is specifying the relevant geographic market. In the baseline analysis, I define markets at the county level, consistent with prior studies that use counties as the unit of analysis for nursing home competition, Medicaid reimbursement policy, and access to care (e.g., Grabowski, 2008; Grabowski et al., 2004; Lin, 2015). Counties are administratively meaningful units because state and local funding decisions, Medicaid reimbursement rates, and regulatory oversight are typically organized along county or sub-county lines. Moreover, county-level indicators of socioeconomic composition, health resources, and utilization are readily available,

facilitating the integration of market-level covariates.

I acknowledge that county boundaries do not perfectly correspond to the actual geographic scope of residents' care-seeking behavior. Some studies instead define markets using fixed or variable radii (e.g., 5-, 10-, or 15-mile catchment areas) around each facility to approximate travel distances and cross-county spillovers (Bowblis & Vassallo, 2014; Rahman et al., 2013). Each approach has trade-offs. Radius-based definitions better reflect patient flow and local competition, but may be sensitive to population density and border effects. In contrast, county-level definitions provide administrative coherence and temporal consistency.

My choice to adopt the county-level definition follows the reasoning in Bowblis and North (2011), who find that county boundaries generally approximate the effective markets for Medicare-reimbursed SNF care, particularly in metropolitan and micropolitan areas. Nonetheless, to ensure robustness, I re-estimate all models using alternative distance-based market definitions—specifically, fixed radii of 5, 10, and 15 miles around each closed facility Table A7–Table A8.

Facilities located in counties that experienced at least one nursing home closure during the study period are classified as the treatment group, while facilities in counties without any closures serve as the control group. For counties that experienced multiple closures between 2011 and 2017, I focus on the first closure event and treat incumbent nursing homes within that county as exposed to closure. This approach facilitates a clean delineation between treatment and control observations while minimizing bias from repeated or overlapping events. As a robustness check, I re-estimate the models restricting the sample to counties that experienced exactly one closure and no new facility entrants during the study period, isolating the effects of a single closure event.

3.3.2 Outcome Variables

The primary outcomes capture both operational and clinical consequences of nursing home closures. At the facility level, I examine two key operational outcomes: (1) occupancy rate and (2) staffing intensity, measured as hours per resident day (HPRD) for certified nursing assistants (CNAs), licensed practical nurses (LPNs), and registered nurses (RNs). Occupancy reflects the balance between local demand and available supply and is sensitive to market contractions or expansions. Staffing levels are central determinants of care quality and a proximate mechanism through which closures may affect residents' well-being (Harrington et al., 2012, 2020; Hyer et al.,

2011).

At the clinical level, I construct a set of facility-level aggregated health outcome measures derived from the Minimum Data Set (MDS) 3.0. The MDS is a federally mandated clinical assessment completed at admission, quarterly, annually, and upon a significant change in condition. To maintain temporal consistency, I use quarterly and annual assessments, aggregating individual-level data to the facility-year level, which yields average indicators that reflect the clinical profile of residents in each nursing home (e.g., Hawes et al., 1997; Rahman et al., 2013, 2014).

I construct two key facility-level outcome measures that capture the overall health status of residents: mortality rate and hospitalization rate. The mortality rate is calculated as the share of residents discharged due to death within a facility-year, while the hospitalization rate is defined as the share of residents discharged to an acute hospital within the same period. Both measures are derived from resident-level discharge records ($A2100$) and serve as broad indicators of resident well-being and care quality.

The clinical measures are organized into active diagonoses domains consistent with the MDS 3.0 structure. This group identifies residents' active clinical conditions based on physician-confirmed diagnoses. Included are Deep Vein Thrombosis ($I0500$), Heart Failure ($I0600$), Pneumonia ($I2000$), Urinary Tract Infection ($I2300$), Wound Infection ($I2500$), Fractures ($I3900 - I4000$), Alzheimer's Disease ($I4200$), Stroke or TIA ($I4500$), Dementia ($I4800$), Anxiety Disorder ($I5700$), Depression ($I5800$), Chronic Lung Disease ($I6200$), and Respiratory Failure ($I6300$). Appendix Table A3 presents the definitions of health outcome variables.

A final refinement in outcome construction involves isolating the spillover effects of nearby closures. To ensure that measured changes reflect the experience of incumbent residents rather than newly admitted individuals from closed facilities, I exclude all MDS assessments associated with residents who transferred following a closure event. Using unique resident identifiers in the MDS, I track individual movements across facilities and omit transferred cases from the analytic sample. Specifically, I exclude residents discharged from a closing facility within 90 days before its closure and subsequently admitted to another nursing home. This approach follows Olenski (2023), ensuring that estimated effects capture the impact of local closures on the health of existing residents, rather than compositional changes in the resident population.

3.3.3 Control Variables

To account for observable differences across facilities, I include a comprehensive set of facility-level control variables, primarily drawn from the Long-Term Care: Facts on Care in the U.S. (LTC-Focus) database. These variables capture structural, demographic, and operational characteristics that may confound the relationship between nursing home closures and subsequent outcomes.

First, I control for ownership type—classified as for-profit or nonprofit—given longstanding evidence that ownership structure is associated with differences in quality, staffing, and financial performance (Comondore et al., 2009; Harrington et al., 2001). I also include indicators for multi-facility affiliation (chain membership) and hospital-based status, as both organizational integration and institutional type can affect financial stability and care practices (Castle et al., 2009).

Second, I adjust for facility size, measured by the total number of certified beds, which serves as a proxy for scale economies and operational capacity. Larger facilities may exhibit greater financial resilience and staffing flexibility relative to smaller ones (Hyer et al., 2011).

Third, I control for resident composition, including the average age of residents, the proportions of female and White residents, and the payer mix—defined as the percentages of residents covered by Medicare and Medicaid. Payer composition is critical because higher Medicaid shares are typically associated with lower reimbursement rates and tighter financial margins, increasing vulnerability to closure (Grabowski et al., 2004; Mor et al., 2004). I also include the Acuindex from LTCFocus, which provides a standardized measure of resident acuity and clinical complexity.

Finally, operational conditions are characterized by the occupancy rate, which reflects local demand relative to capacity, and by staffing resources, measured in terms of certified nursing assistant (CNA), licensed practical nurse (LPN), and registered nurse (RN) hours per resident day (HPRD) (Backhaus et al., 2014; Spilsbury et al., 2011).

To avoid mechanical relationships between dependent and independent variables, I adjust the control specification according to the outcome analyzed. Specifically, when the occupancy rate serves as the dependent variable, the occupancy measure is excluded from the control set. Likewise, when staffing levels are the dependent variables, the corresponding CNA, LPN, and RN HPRD measures are omitted from the model. This ensures that the estimated effects of closure are not confounded by inclusion of the dependent variable on the right-hand side of the regression.

Overall, these controls address systematic differences in ownership, organizational structure, resident demographics, payer composition, case mix, and operating conditions, providing a consistent baseline for estimating the effects of nursing home closures on facility performance and resident outcomes.

3.4 Descriptive Statistics

Table 1 summarizes descriptive statistics comparing facilities located in markets that experienced at least one nursing home closure ("treated") to those in markets without closures ("control") over 2011–2017 (48 contiguous states and DC).

Facilities in closure-affected markets are, on average, larger and more heavily occupied than those in unaffected markets: treated facilities average 121 certified beds and an 84.5% occupancy rate, versus 106 beds and 83.0% in controls. These figures are consistent with consolidation dynamics in more competitive, capacity-constrained settings.

Ownership and organizational characteristics also differ modestly. Approximately 74% of treated facilities are for-profit (vs. 71% in controls); chain affiliation is slightly lower in treated counties (54% vs. 59%), and hospital-based facilities are rare in both groups (3–4%). These patterns align with work showing that independent, for-profit homes are particularly exposed to financial and operational pressures (Castle et al., 2009).

Regarding resident composition, treated markets serve a slightly younger population on average (79.8 vs. 80.9 years) with smaller shares of females (68% vs. 70%) and White (76% vs. 85%). Payer mix is similar across groups (Medicaid $\sim$62%, Medicare $\sim$15%). The LTCFocus acuity index averages 12.0 among treated facilities and 11.9 in controls, indicating marginally higher clinical complexity in treated markets.

Staffing levels are comparable but slightly higher in treated facilities: CNA HPRD 2.39 vs. 2.32; LPN HPRD 0.85 vs. 0.82; RN HPRD 0.46 vs. 0.40. This is consistent with evidence that competitive pressure and higher case-mix intensity are associated with somewhat greater staffing resources (Hyer et al., 2011).

At the market level, treated counties are larger and more urban: average population $\approx$1.6 million versus 218,000 in controls, and much lower Herfindahl-Hirschman Index (HHI) (0.07 vs. 0.31), indicating denser provider competition (Lin, 2015). Treated markets also have younger

populations (13.5% aged 65+ vs. 15.3%) and greater racial diversity (White share 62% vs. 77%). Median household income is higher in treated counties ($52,147 vs. $47,096), and dual-eligibility rates are modestly higher (25.0% vs. 21.8%).

Taken together, these patterns suggest that, in this sample, closures tend to be observed in more urban, competitive markets characterized by larger facilities, slightly higher acuity, and greater racial diversity. In contrast, facilities in rural or less competitive markets—while smaller and less diverse—appear more insulated from closure pressures.[1]

4 Empirical Strategy

4.1 Staggered Difference-in-Differences Framework

In this study, the treatment—nursing home closure—is not introduced simultaneously across all markets. Instead, closures occur at different points in time across counties. This staggered adoption pattern generates a quasi-experimental setting: once a county experiences its first closure, it remains treated in all subsequent years, while other counties may become treated later or remain untreated throughout the study period. Consequently, treatment timing is heterogeneous, and the composition of treated and control groups evolves over time.

In a conventional two-way fixed effects (TWFE) difference-in-differences (DID) framework, such heterogeneity can lead to bias when treatment effects vary across cohorts or over time. As shown by Goodman-Bacon (2021) and De Chaisemartin and d'Haultfoeuille (2020), the standard TWFE estimator is a weighted average of many two-by-two comparisons across timing cohorts and controls, with weights that can be non-convex or even negative. Under staggered closures, later-treated counties may serve as controls for earlier-treated ones ("not-yet-treated"), contaminating control groups and distorting average effects when treatment effects are heterogeneous.

To address this, I adopt the estimator of Callaway and Sant'Anna (2021), which explicitly accounts for staggered timing. The Callaway–Sant'Anna (CS) framework identifies group-time average treatment effects, $ATT_{g,t}$, where g denotes the first-treatment cohort and t denotes calendar time. For each cohort g and time t, treated units are compared to counties that are not yet treated

[1]This characterization is specific to the composition of "treated" versus "control" counties in Table 1. Prior research finds that although absolute numbers of closures are often larger in metro areas (given a larger facility base), closure rates can be higher in non-metropolitan markets (Sharma et al., 2021).

(or never treated) in period t, ensuring comparisons against truly untreated observations. Cohort-specific effects are then aggregated using a convex weighting scheme:

$$ATT^{O} = \sum_{g} w_g \, ATT_g, \qquad ATT_g = \sum_{t \geq g} \omega_{g,t} \, ATT_{g,t},$$

where w_g is proportional to cohort size and $\omega_{g,t}$ are nonnegative time-aggregation weights within cohort g. This approach allows treatment effects to vary flexibly across groups and over time, resolves negative-weight issues in TWFE, and yields consistent average causal effects under standard DID assumptions.

In practice, I implement CS-DID on the sample defined below. Each county enters in the year before its first closure and remains thereafter. Standard errors are clustered at the county level to account for within-county serial correlation (Bertrand et al., 2004; Cameron & Miller, 2015). For robustness, I also report estimates from alternative staggered-adoption estimators that recover dynamic effects under heterogeneity, including Sun and Abraham (2021).

4.2 Matched Difference-in-Differences Framework

Because nursing home closures are not randomly distributed across markets, treated and untreated counties may differ systematically in observable characteristics. To mitigate this non-random selection, I employ propensity score matching (PSM) to construct a balanced comparison sample of treated and control counties (Austin, 2009; Ho et al., 2011; Rosenbaum & Rubin, 1983; Stuart, 2010).

Matching is conducted at the county level, which defines the market throughout the analysis. I estimate propensity scores using a logistic model that predicts the probability of a county experiencing a closure as a function of pre-closure market characteristics, including market concentration (Herfindahl-Hirschman Index (HHI)), total population, the share aged 65+, racial composition, Medicare and Medicaid coverage shares, and median household income. These variables capture demand- and supply-side factors that influence a market's vulnerability to nursing home contraction. I implement optimal matching that minimizes overall imbalance and restricts comparisons to the region of common support (Crump et al., 2009; Hansen & Klopfer, 2006).

Table 1 reports descriptive statistics for the matched treated and control counties. After match-

ing, most facility-level characteristics—including occupancy, bed size, ownership, chain affiliation, and staffing intensity—are well aligned across groups. Payer mix and resident acuity are also balanced, indicating that the matched sample provides a credible basis for comparing post-closure outcomes. At the market level, treated counties remain somewhat larger and more urban, with lower shares of the White population and higher reliance on Medicaid. These residual differences are addressed by including county and year fixed effects, as well as time-varying covariates, in the subsequent difference-in-differences estimation.

4.3 Event Study Design

To test the parallel trends assumption and examine the dynamics of closure effects, I estimate the following event-study specification:

$$Y_{ft} = NHClosure_f \times \sum_{\delta=-3}^{-2} r_\delta \, I(t - t_f^* = \delta) \; + \; NHClosure_f \times \sum_{\delta=0}^{2} \beta_\delta \, I(t - t_f^* = \delta) \\ + \; \alpha X_{ft} \; + \; \theta_c \; + \; \tau_t \; + \; \varepsilon_{ft}, \tag{1}$$

where Y_{ft} is the outcome for facility f in year t, and t_f^* is the year of the first closure in its county. The model includes time-varying controls X_{ft}, county fixed effects θ_c, and year fixed effects τ_t. Indicators $I(t - t_f^* = \delta)$ measure time relative to the closure event, with coefficients r_δ capturing pre-treatment dynamics and β_δ capturing post-treatment effects. Periods beyond three years before and two years after the closure are pooled to avoid sparsity, and the omitted period ($\delta = -1$) is the year immediately preceding closure.

Because treatment is adopted at different times across counties (staggered adoption), I estimate dynamic effects using the interaction-weighted event-study estimator of Sun and Abraham (2021), which (i) compares treated units only to not-yet-treated or never-treated counties in each period and (ii) aggregates cohort-specific lead/lag coefficients with nonnegative weights. This avoids the negative or inappropriate weighting problems of conventional TWFE event studies under heterogeneous effects. In robustness checks, I also report event-time profiles implied by the CS-DID framework (Callaway & Sant'Anna, 2021).

Inference clusters standard errors at the county level to account for serial correlation within markets (Bertrand et al., 2004; Cameron & Miller, 2015). If the pre-treatment coefficients r_δ

are statistically indistinguishable from zero, that supports (but does not prove) parallel trends; I therefore complement conventional pre-trend tests with sensitivity analyses that allow for bounded violations of parallel trends (Rambachan & Roth, 2023).

4.4 Heterogeneity Analysis

To explore heterogeneity in how local markets and facilities respond to nearby closures, I construct several subsamples based on market structure, ownership, organizational affiliation, and payer composition. These classifications allow me to assess whether competitive pressure, profit orientation, organizational structure, and financial dependence on Medicaid moderate the effects of closures on capacity and quality outcomes.

I first classify local nursing home markets as either competitive or concentrated according to the Herfindahl–Hirschman Index (HHI) of facility bed shares within a county. Markets with an HHI below 0.15 are designated as competitive, indicating a relatively fragmented market with multiple comparable providers. In contrast, markets with an HHI of 0.15 or greater are classified as concentrated, where a small number of facilities dominate local capacity. This distinction follows standard antitrust and health economics conventions for market concentration and captures differences in the extent of competitive pressure faced by surviving facilities (U.S. Department of Justice & Federal Trade Commission, 2023).

Within each market type, I distinguish facilities by ownership status. Facilities identified as for-profit are those operated by private, investor-owned entities, while all others–including nonprofit and government-owned facilities–are grouped as nonprofit. Ownership form may shape how facilities respond to market shocks, as for-profit homes generally face stronger profit incentives and may prioritize occupancy and cost containment over staffing intensity or quality investments. Nonprofit facilities, in contrast, may maintain higher staffing ratios or absorb displaced residents differently due to mission-driven objectives and alternative financing structures.

I further categorize facilities by their organizational structure, distinguishing between chain-affiliated and independent providers. A facility is considered chain-affiliated if it belongs to a multi-facility organization, as reported in the CMS Provider of Services file. Chain membership can influence both resource flexibility and managerial response to closures: multi-facility systems can reallocate staff and residents across locations, potentially buffering the impact of local market

shocks. Independent facilities, lacking such network support, may experience greater strain when nearby facilities close.

Finally, I classify facilities according to their reliance on Medicaid. Facilities with at least 70 percent of residents whose primary payer is Medicaid are defined as high-Medicaid, while those below that threshold are categorized as low-Medicaid. This cutoff captures substantial variation in financial exposure to Medicaid reimbursement rates, which remain substantially lower than private-pay or Medicare rates. Facilities serving predominantly Medicaid residents often operate with tighter margins and limited capacity to adjust staffing or absorb new residents following a closure. Comparing high- and low-Medicaid facilities thus provides insight into whether financial vulnerability mediates the effects of market contraction.

These subsample definitions are applied consistently throughout the heterogeneity analysis to test whether the impacts of nursing home closures differ across structural and financial dimensions of the long-term care market.

4.5 Robustness Checks

To evaluate the robustness and interpretability of the estimated effects, I conduct several complementary analyses. First, I re-estimate the main difference-in-differences model without covariates. Following Angrist and Pischke (2009) and Gelbach (2016), this unadjusted specification serves as a benchmark for the total intent-to-treat effect of nearby closures–including indirect channels operating through changes in occupancy, staffing, and payer mix. Comparing the unadjusted and controlled models helps separate the total market response from a direct effect net of these operational mediators.[2] A substantial attenuation of coefficients after adding controls would indicate that closures influence quality primarily via facility-level adjustments rather than direct clinical deterioration.

Second, to isolate the impact of a single closure event, I restrict the sample to counties that experienced exactly one closure during the study period, excluding counties with multiple closures or new entrants (see Appendix Table A5–Table A6). This ensures that estimated effects are not confounded by concurrent entry or overlapping shocks, aligning with best practices for staggered

[2] A formal decomposition of mediation pathways generally requires additional assumptions and methods (e.g., Imai et al., 2010). Here, the adjusted vs. unadjusted contrast is used as an interpretive heuristic rather than as a structural mediation estimate.

adoption settings (Callaway & Sant'Anna, 2021; Sun & Abraham, 2021).

Third, I assess sensitivity to alternative definitions of market exposure. Instead of using county boundaries, I redefine treatment spatially, identifying facilities within 15, 10, or 5 miles of a closed nursing home as treated units (see Appendix Table A7–Table A8). This spatial specification allows examination of how spillover effects decay with distance and whether the main findings are robust to alternative market delineations (Bowblis & North, 2011; Lin, 2015; Rahman et al., 2013).

Across all robustness checks, the estimated effects remain consistent in direction and magnitude, suggesting that the results are not sensitive to model specification, sample composition, or market definition. Consequently, these analyses increase confidence that the main findings reflect genuine adjustments to local market contraction rather than artifacts of specification or sample selection.

5 Results

This section examines how nearby nursing home closures affect the health outcomes of incumbent residents who remain in surviving facilities. I focus on four groups of outcomes–mortality, hospitalization, active diagnoses, and facility mechanisms (occupancy and staffing)–with attention to how effects differ across market concentration.[3] The specification with covariate controls serves as the baseline model, while unadjusted estimates capture total (unmediated) effects, and matched-sample estimates serve as robustness checks for selection on observables.

5.1 Mortality

Mortality rate is defined as the share of residents in a facility-year whose MDS discharge record ($A2100$) indicates deceased. This measure, therefore, captures the in-facility mortality rate among all residents present during the year. Deaths following external transfers (e.g., hospitalizations) are not captured in this measure.

Panel B of Table 2 and Figure 1 show that nearby closures do not increase mortality among incumbents. In the baseline specification, the coefficient is -0.185 ($p = 0.02$), indicating a small but statistically significant decline in facility-level mortality following a local closure. Relative to the

[3]The Herfindahl-Hirschman Index (HHI) thresholds follow U.S. antitrust (DOJ/FTC) merger guidelines. With HHI normalized to $[0, 1]$: < 0.15 is competitive and 0.15–1 is concentrated (U.S. Department of Justice & Federal Trade Commission, 2023).

pre-closure mean mortality rate of 12.8 percent, this corresponds to roughly a 1.4 percent reduction in mortality. The matched-sample estimate (-0.135) is similar in magnitude but less precise (about a 1 percent decline relative to the same baseline), reinforcing the robustness of the result.

The event-study estimates in Figure A2 confirm this pattern: mortality remains stable in the pre-period, validating the parallel-trend assumption, and declines immediately after the closure year. The effect stabilizes over the subsequent two years, suggesting a persistent, modest improvement in survival rates rather than a short-lived adjustment. When disaggregated by market structure, Figure A2 shows that the decline is driven entirely by competitive markets, where post-closure mortality falls by 0.2–0.3 percentage points, or roughly 1–2 percent of the pre-closure mortality rate. In contrast, concentrated markets exhibit flat or slightly positive coefficients (e.g., 0.066 on a baseline mean of 16.0 percent, about a 0.4 percent increase), indicating that any mortality benefits are offset when capacity constraints tighten.

Thus, while closures are generally not harmful, the dynamic evidence underscores a key asymmetry: competitive markets absorb closure shocks smoothly, whereas concentrated markets face sustained stress that erodes potential gains.

5.2 Hospitalization

Hospitalization rate is also constructed from the MDS discharge record ($A2100$) as the share of residents whose record was classified as an acute hospital transfer. This outcome reflects the annual rate of hospital transfers among all residents, reflecting acute-care utilization closely linked to nursing home quality and care coordination.

As shown in Panel B of Table 2 and Figure 1, the average effect of nearby closures on hospitalization is small and statistically insignificant (0.374, s.e. $= 0.231$). Given a pre-closure mean hospitalization rate of 38.2 percent, this coefficient corresponds to an increase of just under 1 percent of the baseline rate. This suggests no systematic shift toward hospital-based care following closures. Yet, once disaggregated by market structure, divergent patterns emerge. In competitive markets, hospitalization remains essentially unchanged (0.322 on a baseline of 38.4 percent, roughly a 0.8 percent increase), whereas in concentrated markets, the sign flips slightly negative (-0.037 on a baseline of 37.3 percent, about a 0.1 percent decline) but with large standard errors.

The event-study plots in Figure A2 support this interpretation. The coefficients hover around

zero before the closure, confirming parallel trends, but show a short-lived rise in the closure year (t = 0) followed by reversion toward zero. In competitive markets, this transitory increase is more pronounced–suggesting temporary reliance on hospital transfers as facilities adjust to new resident inflows–whereas in concentrated markets, hospitalization briefly dips, consistent with tighter capacity and potential under-referral. Together with the mortality findings, this pattern implies that surviving facilities in competitive markets buffer short-run disruptions through flexible reallocation, while those in concentrated markets may suppress hospital transfers amid staffing strain.

5.3 Active Diagnoses

To investigate broader health dimensions, I estimate effects on a set of physician-documented active diagnoses recorded in Section I of the MDS. Each diagnosis indicator is originally coded at the resident-assessment level as a binary variable equal to one if the condition was active within the reference period–typically seven days (thirty days for urinary tract infection). I aggregate these indicators to the facility-year level by computing the share of all MDS assessments in which the condition was documented as active. Thus, each outcome represents the proportion of assessments reporting the diagnosis. These indicators cover major cardiovascular, respiratory, infectious, musculoskeletal, and neuropsychiatric conditions, defined in Table A3. Higher values indicate greater disease prevalence, so negative coefficients reflect improvements in health.

Across the full sample, several infection-related conditions improve following nearby closures. Urinary tract infections ($I2300$) and wound infections ($I2500$) decline significantly (-0.404 and -0.063, respectively). Relative to pre-closure mean prevalence rates of 10.8 percent for UTIs and 1.2 percent for wound infections, these coefficients imply reductions of roughly 3.7 percent and 5.3 percent of the baseline rates. Pneumonia ($I2000$) and DVT ($I0500$) remain largely unchanged in economic terms: the point estimates (-0.030 and 0.079) correspond to changes of about -0.6 percent and +2.5 percent of their baseline means (4.8 and 3.1 percent), and are imprecisely estimated.

The dynamic patterns align with this interpretation. Event-study estimates for infections show a clear downward break at closure and stable post-trends, with sharper declines in competitive markets. In competitive markets, the UTI coefficient of -0.298 on a baseline mean of 10.8 percent corresponds to roughly a 2.8 percent reduction, while wound infections fall by about 3.8 percent of the baseline rate. No pre-trend violations are evident, reinforcing causal interpretation. By contrast,

some chronic and cardiovascular diagnoses worsen in concentrated markets. Heart failure ($I0600$) and respiratory failure ($I6300$) show upward drifts beginning one year after closure, consistent with cumulative strain on clinical management. For example, in concentrated markets the heart failure coefficient of 0.674 on a baseline mean of 22.5 percent represents about a 3 percent increase, and the respiratory failure coefficient of 0.190 on a baseline mean of 1.8 percent implies an increase of roughly 10–11 percent of the baseline rate. These effects are absent or muted in competitive markets.

Neuropsychiatric conditions exhibit the opposite trend. Alzheimer's disease and dementia ($I4200$, $I4800$) decline steadily after closure in competitive markets, while anxiety and depression ($I5700$, $I5800$) also fall modestly. For instance, the competitive-market estimate for dementia of about -0.9 percentage points on a baseline mean of 38.3 percent corresponds to roughly a 2–3 percent decline, and the depression coefficient of -0.476 on a baseline mean of 46.1 percent implies about a 1 percent reduction. In concentrated markets, however, coefficients flatten or rebound, suggesting that cognitive and mental health benefits are market-contingent.

Overall, the event-study evidence reinforces a clear structural asymmetry: competitive environments amplify the positive spillovers of exit–reducing infections and psychological distress–while concentrated markets experience worsening in resource-intensive chronic conditions. These results are summarized in Table 2 and visualized in Figure 1, where all effects are scaled as percentages of pre-closure means.

5.4 Mechanisms: Occupancy and Staffing

Finally, I examine facility-level mechanisms that may explain the heterogeneous health effects observed above. Two key outcomes are occupancy rates and staffing intensity. Occupancy is defined as the ratio of the average daily census to total certified bed capacity. Staffing variables–CNA, LPN, and RN hours per resident day–correspond to the average number of care hours delivered per resident per day during the year.

Across the full sample, nearby closures significantly increase occupancy and reduce staffing intensity, consistent with surviving facilities absorbing displaced residents without proportionate labor adjustments. The baseline estimates in Table 3 and Figure 2 show that occupancy rises by roughly 1.5–2 percentage points when expressed in levels. In the specification scaled to pre-

closure means (Panel B), the overall occupancy coefficient of 0.345 on a baseline mean of 83.3 percent corresponds to an increase of about 0.4 percent of the baseline occupancy rate, while in concentrated markets the coefficient of 1.126 on a baseline mean of 80.7 percent implies an increase of about 1.4 percent. CNA and LPN hours per resident day decline modestly (about 0.02–0.04 hours in level terms), which in the scaled specification translates into changes on the order of -0.3 to +1.5 percent of their baseline means. RN hours fall more sharply, by approximately 0.07–0.10 hours per resident day in levels; the Panel B estimate of -0.009 on a baseline mean of 0.5 hours corresponds to roughly a 1.8 percent reduction in RN staffing overall, and the matched-sample concentrated-market estimate of -0.020 on a baseline mean of 0.4 hours implies a decline of about 5 percent of the baseline RN intensity (Spilsbury et al., 2011).

The event-study plots in Figure A3 corroborate these aggregate effects, showing no pre-trend differentials, followed by a discrete rise in occupancy at the time of closure and persistent declines in RN staffing. CNA and LPN hours exhibit smaller and short-lived reductions, consistent with temporary scheduling constraints. Disaggregating by market structure, Figure A3 reveal that concentrated markets experience larger and more sustained changes: occupancy rises sharply and RN hours continue to fall through year +2, with the magnitudes corresponding to roughly 1–2 percent increases in occupancy and 3–5 percent reductions in RN hours relative to pre-closure means. In competitive markets, by contrast, both effects are moderate and transient, on the order of a few tenths of a percent of baseline staffing and occupancy.

These heterogeneous patterns are consistent with theoretical predictions about market structure in long-term care (Bowblis & Vassallo, 2014). In concentrated or rural markets, where facilities are few and often capacity-constrained, a closure can tighten occupancy and labor pressures, reducing operational flexibility and ultimately leading to quality declines. By contrast, in competitive or urban markets, closures may primarily eliminate low-quality or financially fragile providers, thereby improving the efficiency and average quality of the remaining facilities. The empirical results presented here confirm this heterogeneity, showing that efficiency-enhancing reallocation dominates in competitive areas, whereas resource strain and quality deterioration emerge in concentrated ones.

5.5 Heterogeneity by Facility Characteristics

To assess how financial and organizational capacity mediate the effects of nearby closures, I examine heterogeneity by ownership, chain affiliation, and Medicaid payer mix, each interacted with market concentration. This 2x2 design (e.g., competitive–profit, concentrated–profit, competitive–nonprofit, concentrated–nonprofit) highlights how market structure moderates institutional responses. Table 4 and Table 5 summarize the corresponding regression results, while Figure 3, Figure 4, Figure 5 and Figure 6 visualize the estimated coefficients (ATT as % of mean) and their 90% confidence intervals.

Ownership (for-profit vs. nonprofit). The effects of nearby closures diverge sharply by ownership. Nonprofit nursing homes experience clear improvements in several health indicators–particularly urinary tract infection, dementia, and depression–suggesting better post-closure care. For example, in competitive markets the nonprofit estimates for dementia and depression correspond to reductions on the order of 2–3 percent and about 1 percent of their pre-closure means, respectively. In contrast, for-profit homes exhibit little or no overall improvement, and in some cases modest deterioration. This pattern implies that ownership mediates the capacity to translate market shocks into quality improvements, consistent with prior evidence that nonprofit facilities provide higher-quality care and reinvest more in resident well-being rather than cost containment (e.g., Comondore et al., 2009; Harrington et al., 2001).

Organizational structure (chain vs. independent). Chain-affiliated and independent facilities remain broadly resilient across all market types. Health outcomes are broadly similar, indicating that organizational structure alone does not systematically alter resident well-being after nearby closures. However, concentrated-chain nursing homes experience a larger rise in occupancy but no corresponding deterioration in quality. The occupancy estimates imply increases of roughly 1–2 percent of pre-closure occupancy in concentrated-chain facilities, whereas independent facilities show smaller and less precisely estimated changes. This buffering capacity likely reflects shared management and staffing resources within multi-facility organizations.

Payer mix (high vs. low Medicaid). Financial dependence on Medicaid amplifies disparities in adjustment. Health outcomes diverge clearly by Medicaid dependence, even though mechanisms such as occupancy and staffing show little variation across groups. In competitive markets, low-Medicaid nursing homes exhibit modest improvements in resident health–particularly lower infection and neuropsychiatric diagnoses–with estimated effects typically on the order of 2–4 percent of pre-closure means for conditions such as UTIs and depression. High-Medicaid facilities show little change. In concentrated markets, by contrast, high-Medicaid homes experience worsening conditions, including higher rates of depression and respiratory illness: for example, the concentrated high-Medicaid respiratory-failure coefficient implies roughly a 10 percent increase relative to its already low baseline prevalence. Low-Medicaid facilities in the same markets remain largely stable. These patterns indicate that fiscal capacity is a key determinant of resilience: financially stronger, low-Medicaid facilities can absorb closure shocks without compromising care, whereas high-Medicaid homes, already operating under tight resource constraints, are more vulnerable to quality deterioration.

6 Conclusion

This paper examines how nearby nursing home closures affect the health and care of incumbent residents who remain in surviving facilities. Using comprehensive resident-level data from the Minimum Data Set linked to facility and county characteristics, I employ a staggered difference-in-differences framework with event-study diagnostics to identify the causal effects of closure exposure on a wide range of resident outcomes. By focusing on non-displaced residents, the analysis isolates spillover effects on those who stay, thereby revealing how local market structure mediates the reallocation of care within long-term care systems.

The findings reveal substantial heterogeneity across market environments. In thin or capacity-constrained markets, where facilities are few and labor supply is limited, the exit of a single provider can destabilize the local care network, strain staff resources, and erode quality. In better-served and more competitive markets, however, exit can promote reallocation toward higher-quality and more efficient facilities. The causal evidence thus demonstrates that market concentration is a key moderating force: the same closure shock can yield either beneficial or adverse spillovers depending

on the availability of substitute capacity.

Beyond market structure, the analysis also reveals important heterogeneity across facility types. Nonprofit, chain-affiliated, and low-Medicaid nursing homes demonstrate greater resilience to nearby closures, maintaining or improving resident health, whereas for-profit, independent, and high-Medicaid facilities–typically operating with tighter margins and limited staffing flexibility–show weaker or adverse responses. These differences suggest that organizational form and financial capacity shape how facilities absorb market shocks, mediating whether closures lead to efficiency gains or quality losses. Policies aimed at supporting financially vulnerable and independent facilities, particularly those with high Medicaid dependence, may therefore be crucial to preserving equity and stability in the long-term care system.

From a policy perspective, these findings underscore the need for targeted responses when nursing homes close. In well-served urban or competitive regions, regulators and policymakers may focus on facilitating smooth transitions and even allow or encourage consolidation that improves efficiency without compromising quality. In contrast, in rural or capacity-constrained areas, closures can severely disrupt the care continuum, requiring proactive interventions to safeguard resident welfare. Policymakers could consider strategies such as increasing Medicaid reimbursement rates in low-margin areas, providing temporary staffing or training grants to remaining facilities after a closure, or offering incentives for new facility entry or expansion in high-need regions. Relaxing restrictive Certificate-of-Need (CON) regulations could also encourage new investment where capacity is most limited (Hackmann, 2019; Park & Werner, 2011; Rahman et al., 2016). Together, these measures would help ensure that older adults in vulnerable communities maintain access to quality care even amid structural contraction.

Overall, this study provides causal evidence that the effects of provider exit are fundamentally heterogeneous: closures can improve quality and efficiency in competitive markets and financially robust facilities, but risk quality deterioration in concentrated or resource-constrained settings. The results highlight the dual nature of reallocation in health care—an essential mechanism for efficiency that, without sufficient local capacity and policy support, can also amplify inequality in access and outcomes.

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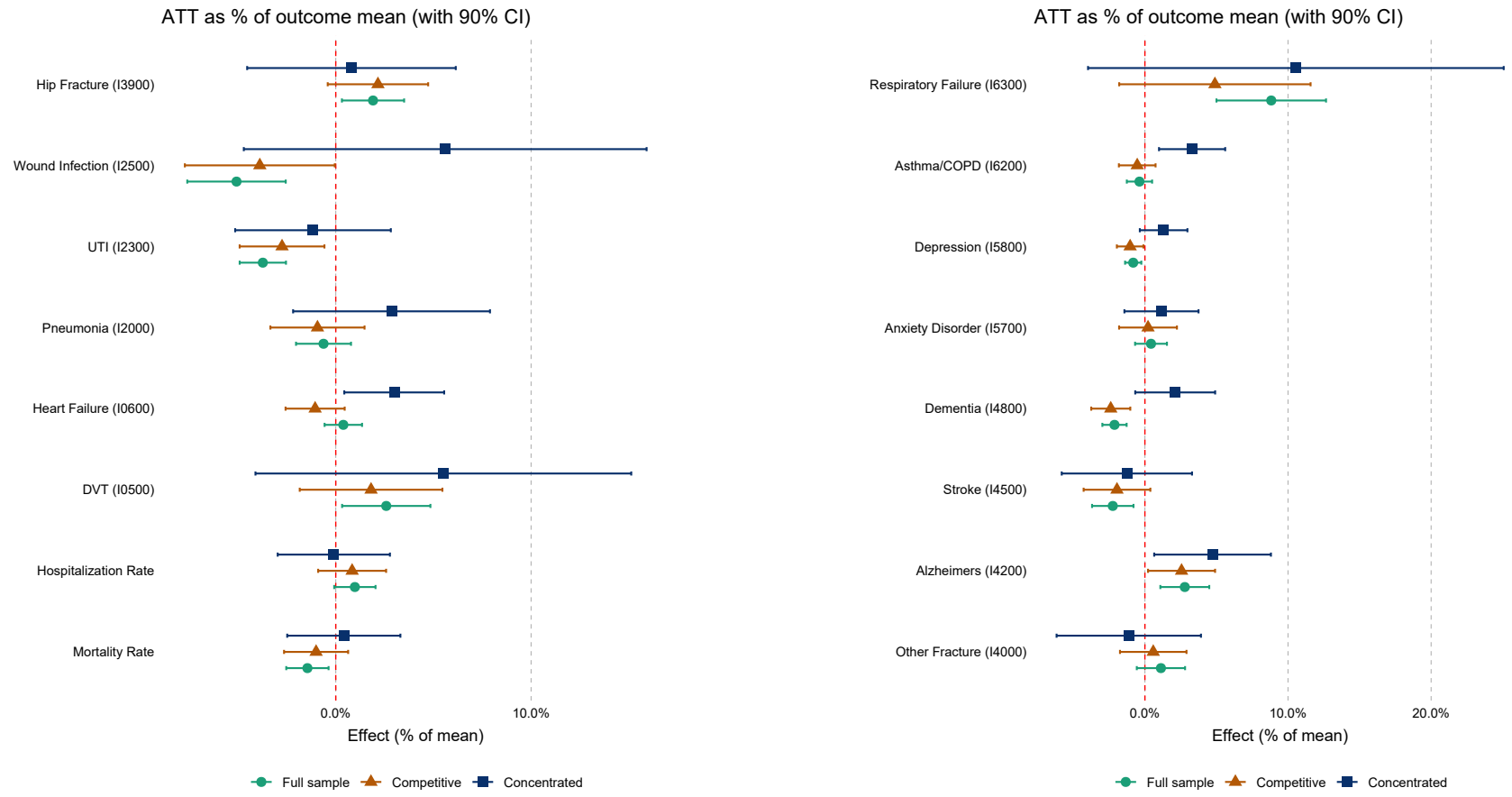
Figures and Tables

Table 1: Descriptive Statistics: Treated vs. Control vs. Matched Control Nursing Homes (2011)

Variable	Treated			Control			Matched Control		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Facility-level characteristics									
Occupancy rate (%)	5,531	84.52	12.82	8,130	82.97	14.12	3,639	84.79	12.92
Total beds	5,536	121.13	68.46	8,138	105.96	55.13	3,642	118.25	62.81
For-profit ownership (1=yes)	5,536	0.74	0.44	8,138	0.71	0.46	3,642	0.73	0.44
Multi-facility affiliation (1=yes)	5,536	0.54	0.50	8,138	0.59	0.49	3,642	0.60	0.49
Hospital-based (1=yes)	5,536	0.03	0.17	8,138	0.04	0.20	3,642	0.02	0.15
Average resident age	5,490	79.78	7.52	8,096	80.87	5.77	3,627	80.45	6.63
Female residents (%)	5,431	68.23	12.71	8,027	70.08	10.63	3,596	69.68	11.52
White residents (%)	5,350	76.29	25.13	8,039	85.40	19.38	3,590	82.04	20.90
Medicaid residents (%)	5,536	61.99	21.00	8,138	62.30	18.26	3,642	60.96	19.65
Medicare residents (%)	5,536	15.51	12.76	8,138	14.36	11.45	3,642	15.76	12.19
Acuity index	5,536	12.02	1.88	8,138	11.86	1.61	3,642	12.10	1.47
CNA hours per resident day	5,532	2.39	0.73	8,129	2.32	0.66	3,638	2.35	0.64
LPN hours per resident day	5,533	0.85	0.45	8,135	0.82	0.51	3,641	0.85	0.55
RN hours per resident day	5,536	0.46	0.43	8,137	0.40	0.42	3,641	0.43	0.42
County-level characteristics									
Herfindahl–Hirschman Index (HHI)	5,592	0.07	0.10	8,214	0.31	0.27	3,675	0.13	0.12
Population	5,592	1,593,803	2,430,347	8,214	217,686	358,944	3,675	417,465	459,935
Population aged 65+ (%)	5,592	13.45	3.22	8,214	15.28	3.85	3,675	14.41	3.93
White population (%)	5,592	62.11	20.85	8,214	76.78	19.06	3,675	71.14	19.87
Dual-eligible share (%)	5,592	25.04	9.99	8,214	21.82	8.10	3,675	21.46	8.18
Median household income ($)	5,592	52,147	11,689	8,214	47,096	12,537	3,675	51,248	13,867
Number of counties		442			2,346			442	

Notes: Facilities are classified as "treated" if located in counties that experienced at least one nursing home closure by 2011; "control" counties had none. "Matched control" counties are selected via optimal propensity score matching at the county level. Variables are measured at the facility level unless otherwise noted. County-level indicators (HHI, population, income, demographics) are from 2011.

Figure 1: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses



Notes: Each panel displays coefficients from separate regressions in Table 2. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Table 2: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses

	Mortality Rate	Hospitalization Rate	DVT (I0500)	Heart Failure (I0600)	Pneumonia (I2000)	UTI (I2300)	Wound Infection (I2500)	Hip Fracture (I3900)
Panel A. No controls								
Full Sample	-0.194**	-0.039	0.067	0.184	-0.065	-0.493***	-0.082***	0.062
	(0.082)	(0.248)	(0.041)	(0.119)	(0.045)	(0.085)	(0.021)	(0.037)
	[N=82,376]	[83,083]	[83,181]	[76,650]	[76,230]	[60,837]	[76,125]	[76,237]
Competitive	-0.130	-0.138	0.038	-0.213	-0.066	-0.292*	-0.054*	0.072
	(0.119)	(0.384)	(0.065)	(0.189)	(0.066)	(0.154)	(0.032)	(0.053)
	[N=40,243]	[40,733]	[40,789]	[35,196]	[35,084]	[31,913]	[35,042]	[35,056]
Concentrated	0.106	0.367	0.122	0.621**	0.196	-0.055	0.098	0.103
	(0.289)	(0.678)	(0.144)	(0.294)	(0.125)	(0.245)	(0.065)	(0.109)
	[N=34,475]	[34,643]	[34,699]	[34,524]	[34,314]	[23,842]	[34,265]	[34,342]
Panel B. With controls								
Full Sample	-0.185**	0.374	0.079*	0.081	-0.030	-0.404***	-0.063***	0.067**
	(0.084)	(0.246)	(0.042)	(0.122)	(0.041)	(0.078)	(0.019)	(0.034)
	[N=74,228]	[74,494]	[74,529]	[69,811]	[69,461]	[55,293]	[69,398]	[69,496]
Competitive	-0.121	0.322	0.057	-0.217	-0.046	-0.298**	-0.050*	0.076
	(0.120)	(0.406)	(0.070)	(0.189)	(0.072)	(0.143)	(0.030)	(0.055)
	[N=36,197]	[36,400]	[36,414]	[32,081]	[31,962]	[28,931]	[31,941]	[31,955]
Concentrated	0.066	-0.037	0.130	0.674*	0.124	-0.125	0.059	0.028
	(0.282)	(0.651)	(0.138)	(0.350)	(0.133)	(0.260)	(0.066)	(0.113)
	[N=31,388]	[31,423]	[31,458]	[31,542]	[31,360]	[21,952]	[31,325]	[31,388]
Panel C. With controls, matched sample								
Full Sample	-0.135	0.393	0.053	-0.004	-0.029	-0.268*	-0.028	0.064
	(0.154)	(0.401)	(0.074)	(0.223)	(0.085)	(0.146)	(0.038)	(0.070)
	[N=46,018]	[46,242]	[46,256]	[41,048]	[40,894]	[35,826]	[40,866]	[40,880]
Competitive	-0.138	0.344	0.047	-0.216	-0.048	-0.306**	-0.055*	0.082
	(0.121)	(0.393)	(0.076)	(0.191)	(0.074)	(0.140)	(0.032)	(0.054)
	[N=35,742]	[35,945]	[35,959]	[31,346]	[31,234]	[28,567]	[31,213]	[31,227]
Concentrated	-0.029	0.479	0.023	0.356	0.096	-0.124	0.053	-0.003
	(0.336)	(0.749)	(0.142)	(0.420)	(0.148)	(0.305)	(0.080)	(0.139)
	[N=9,093]	[9,128]	[9,135]	[8,652]	[8,603]	[6,216]	[8,610]	[8,624]
Baseline mean								
Full Sample	12.8	38.2	3.1	20.9	4.8	10.8	1.2	3.5
Competitive	12.0	38.4	3.2	20.5	4.9	10.8	1.3	3.5
Concentrated	16.0	37.3	2.4	22.5	4.3	10.7	1.1	3.5

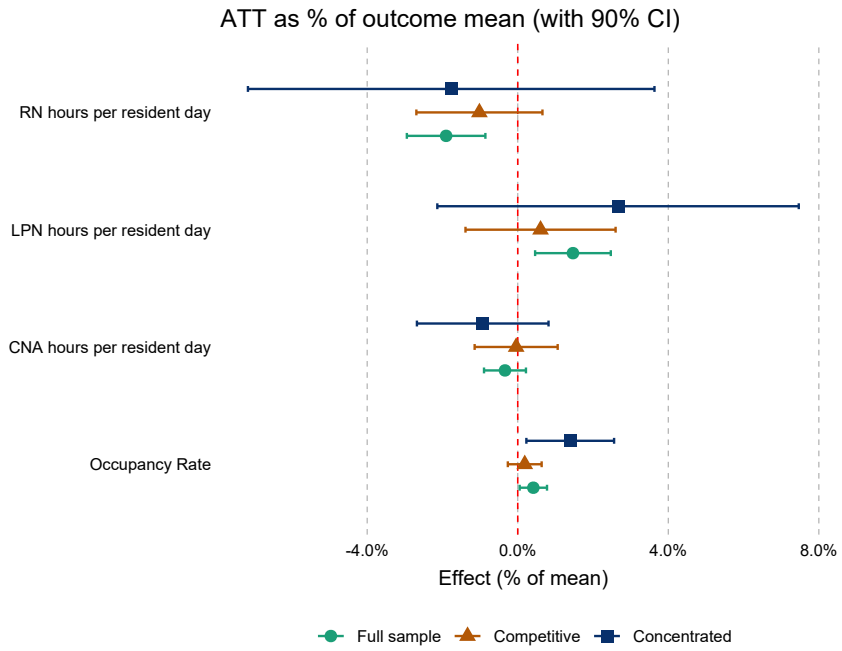
Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

Table 2: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (continued)

	Other Fracture (I4000)	Alzheimers (I4200)	Stroke (I4500)	Dementia (I4800)	Anxiety Disorder (I5700)	Depression (I5800)	Asthma/COPD (I6200)	Respiratory Failure (I6300)
Panel A. No controls								
Full Sample	0.060	0.478***	-0.371***	-0.554***	0.170	-0.314*	-0.099	0.138***
	(0.057)	(0.122)	(0.134)	(0.209)	(0.173)	(0.162)	(0.114)	(0.050)
	[N=76,279]	[82,866]	[76,545]	[76,769]	[81,529]	[76,790]	[76,699]	[76,160]
Competitive	0.022	0.378*	-0.325	-0.595**	0.127	-0.418*	-0.123	0.091
	(0.076)	(0.197)	(0.223)	(0.281)	(0.301)	(0.250)	(0.156)	(0.113)
	[N=35,105]	[40,621]	[35,161]	[35,259]	[40,019]	[35,273]	[35,245]	[35,063]
Concentrated	-0.022	0.747**	-0.152	0.649	0.216	0.547	0.554*	0.198
	(0.147)	(0.322)	(0.367)	(0.476)	(0.414)	(0.418)	(0.324)	(0.165)
	[N=34,321]	[34,608]	[34,482]	[34,559]	[34,006]	[34,566]	[34,531]	[34,272]
Panel B. With controls								
Full Sample	0.059	0.357***	-0.357**	-0.816***	0.103	-0.381**	-0.084	0.239***
	(0.054)	(0.133)	(0.140)	(0.198)	(0.163)	(0.161)	(0.119)	(0.063)
	[N=69,510]	[74,431]	[69,727]	[69,860]	[73,619]	[69,867]	[69,825]	[69,398]
Competitive	0.031	0.322*	-0.315	-0.914***	0.051	-0.476*	-0.119	0.142
	(0.075)	(0.179)	(0.229)	(0.318)	(0.287)	(0.260)	(0.173)	(0.118)
	[N=31,983]	[36,365]	[32,032]	[32,109]	[36,050]	[32,116]	[32,095]	[31,941]
Concentrated	-0.058	0.654*	-0.182	0.817	0.320	0.643	0.732**	0.190
	(0.158)	(0.343)	(0.400)	(0.655)	(0.435)	(0.497)	(0.312)	(0.159)
	[N=31,374]	[31,416]	[31,514]	[31,563]	[31,024]	[31,563]	[31,542]	[31,325]
Panel C. With controls, matched sample								
Full Sample	0.046	0.353*	-0.305	-0.698*	0.145	-0.299	-0.009	0.143
	(0.110)	(0.205)	(0.244)	(0.402)	(0.291)	(0.301)	(0.219)	(0.097)
	[N=40,915]	[46,193]	[40,999]	[41,062]	[45,745]	[41,069]	[41,062]	[40,866]
Competitive	0.029	0.300	-0.276	-0.884***	0.038	-0.458*	-0.117	0.133
	(0.078)	(0.188)	(0.221)	(0.334)	(0.303)	(0.264)	(0.163)	(0.119)
	[N=31,255]	[35,910]	[31,304]	[31,367]	[35,609]	[31,374]	[31,367]	[31,213]
Concentrated	-0.194	0.402	0.191	0.196	0.237	0.631	0.571	0.267
	(0.186)	(0.409)	(0.504)	(0.826)	(0.525)	(0.610)	(0.442)	(0.180)
	[N=8,610]	[9,114]	[8,638]	[8,659]	[9,009]	[8,659]	[8,659]	[8,603]
Baseline mean								
Full Sample	5.3	12.8	15.9	38.4	24.1	46.6	22.1	2.7
Competitive	5.3	12.6	16.2	38.3	23.4	46.1	22.2	2.9
Concentrated	5.2	13.8	14.5	38.6	27.6	49.1	22.2	1.8

Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

Figure 2: Effects of Nursing Home Closures on Occupancy and Staffing



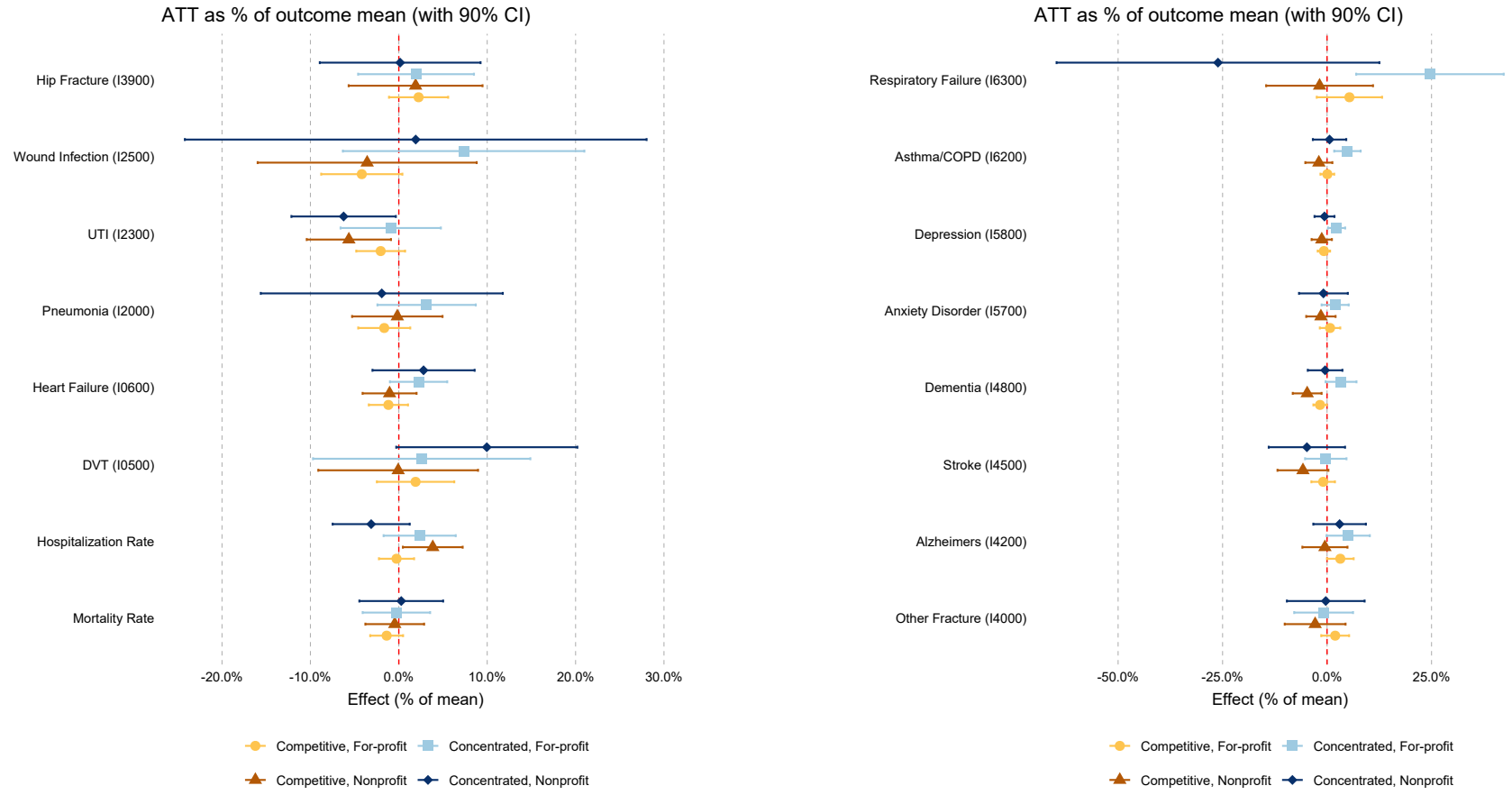
Note: Each panel displays coefficients from separate regressions in Table 3. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Table 3: Effects of Nursing Home Closures on Occupancy and Staffing

	Occupancy Rate	CNA HPRD	LPN HPRD	RN HPRD
Panel A. No controls				
Full Sample	0.758***	-0.002	0.013**	-0.013***
	(0.184)	(0.008)	(0.005)	(0.004)
	[N=83,146]	[82,285]	[81,823]	[81,221]
Competitive	0.483*	-0.003	0.002	-0.007
	(0.248)	(0.014)	(0.010)	(0.007)
	[N=40,971]	[40,621]	[40,292]	[40,033]
Concentrated	1.039*	-0.020	0.003	-0.015
	(0.583)	(0.023)	(0.018)	(0.014)
	[N=34,685]	[34,251]	[34,258]	[33,964]
Panel B. With controls				
Full Sample	0.345*	-0.008	0.012**	-0.009***
	(0.184)	(0.008)	(0.005)	(0.003)
	[N=75,432]	[78,253]	[77,889]	[77,217]
Competitive	0.156	-0.001	0.005	-0.005
	(0.229)	(0.016)	(0.010)	(0.005)
	[N=36,911]	[38,276]	[38,003]	[37,709]
Concentrated	1.126**	-0.021	0.021	-0.007
	(0.572)	(0.024)	(0.023)	(0.013)
	[N=31,773]	[32,844]	[32,872]	[32,564]
Panel C. With controls, matched sample				
Full Sample	0.412	-0.010	0.008	-0.007
	(0.328)	(0.014)	(0.015)	(0.008)
	[N=46,886]	[48,797]	[48,482]	[48,041]
Competitive	0.182	-0.007	0.003	-0.006
	(0.250)	(0.015)	(0.010)	(0.005)
	[N=36,456]	[37,919]	[37,667]	[37,359]
Concentrated	1.154*	-0.027	0.015	-0.020*
	(0.683)	(0.028)	(0.012)	(0.011)
	[N=9,233]	[9,534]	[9,534]	[9,429]
Baseline mean				
Full Sample	83.3	2.4	0.8	0.5
Competitive	83.9	2.4	0.8	0.5
Concentrated	80.7	2.3	0.8	0.4

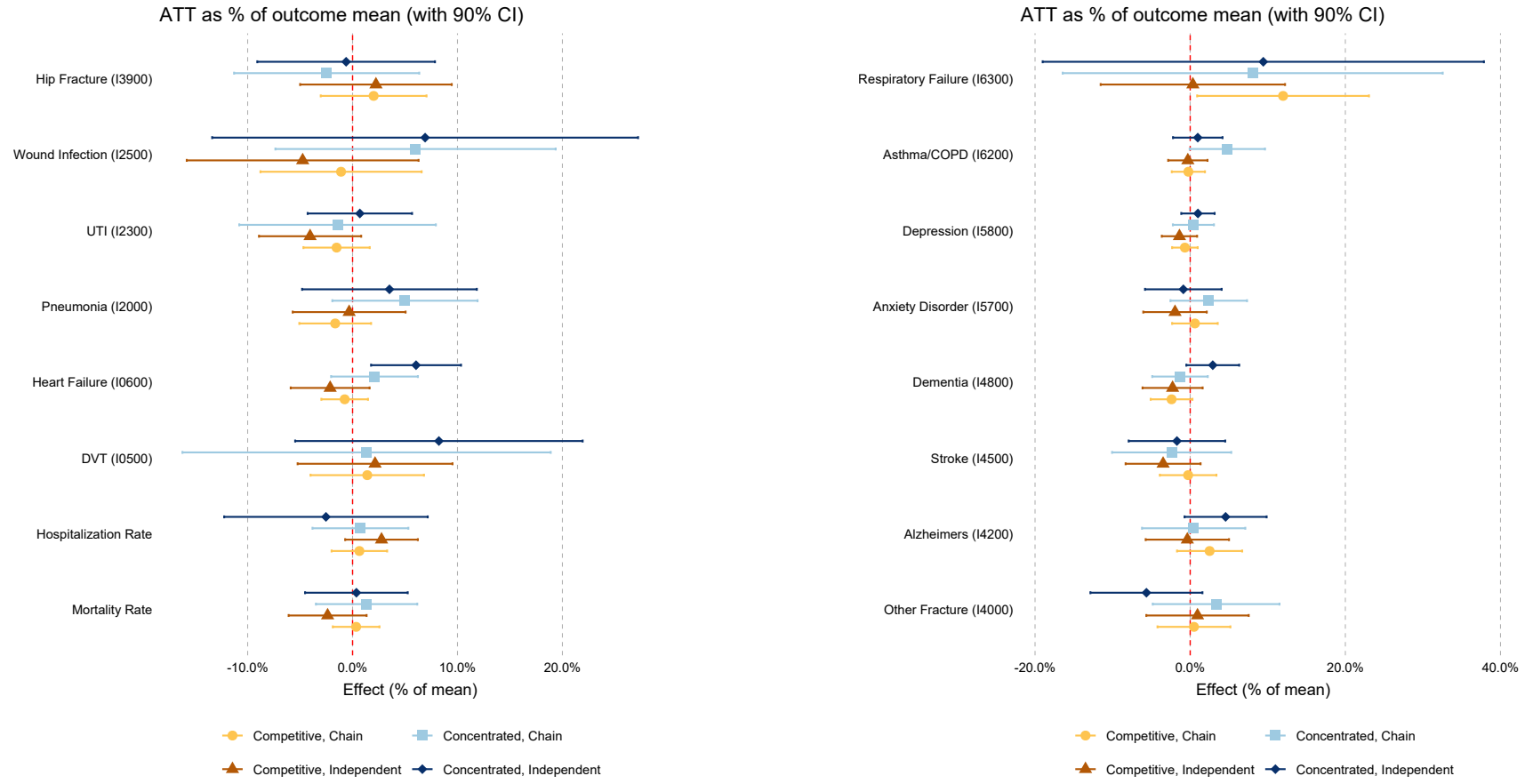
Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

Figure 3: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (by Ownership Type)



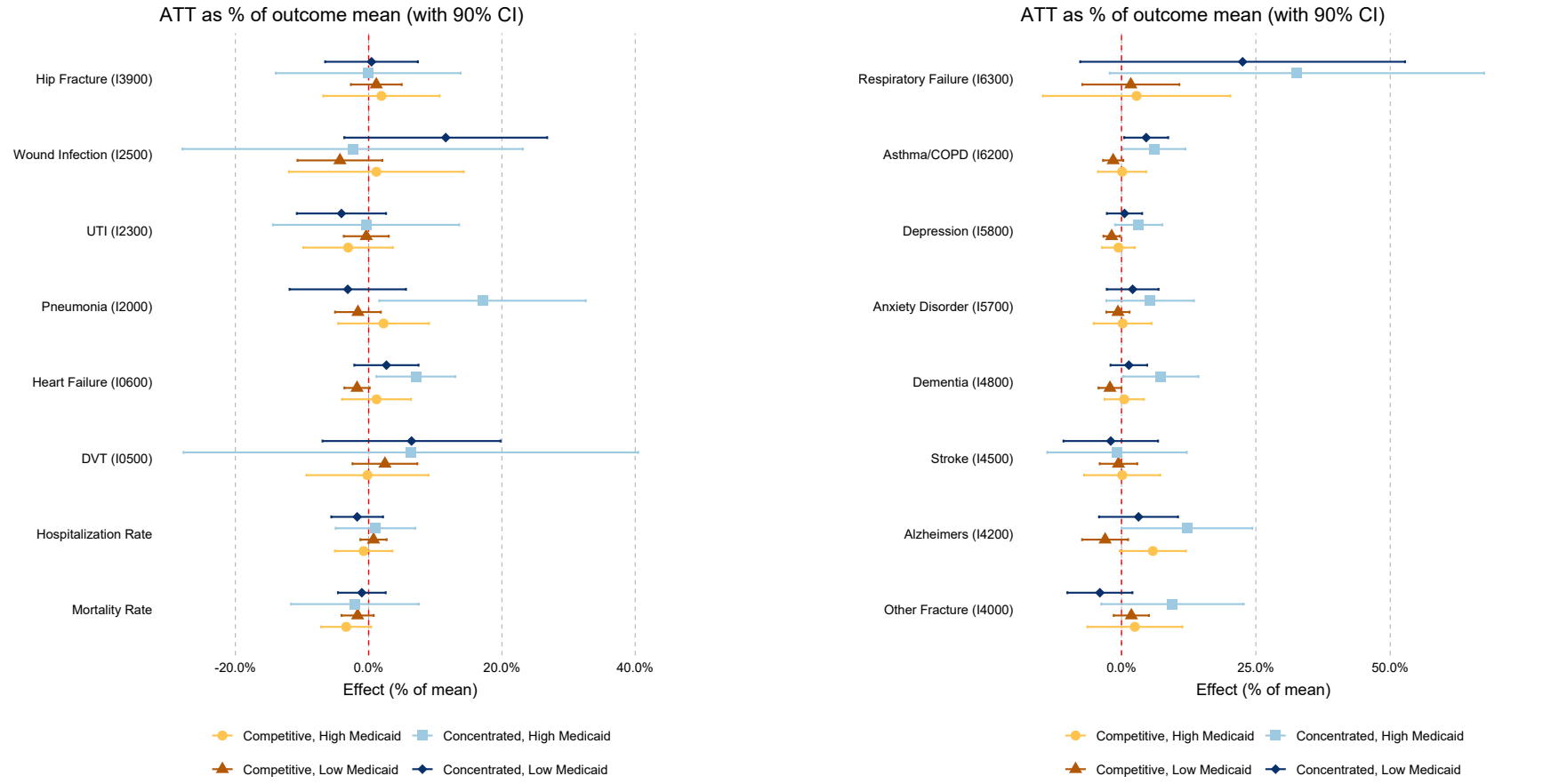
Notes: Each panel displays coefficients from separate regressions in Panel A, Table 4. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Figure 4: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (by Chain Affiliation)



Notes: Each panel displays coefficients from separate regressions in Panel B, Table 4. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Figure 5: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (by Medicaid Share)



Notes: Each panel displays coefficients from separate regressions in Panel C, Table 4. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Table 4: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (by Ownership, Chain, and Medicaid Share)

	Mortality Rate	Hospitalization Rate	DVT (I0500)	Heart Failure (I0600)	Pneumonia (I2000)	UTI (I2300)	Wound Infection (I2500)	Hip Fracture (I3900)
Panel A. Profit vs. Nonprofit								
Competitive, For-Profit	-0.157	-0.105	0.062	-0.237	-0.082	-0.221	-0.057	0.077
	(0.129)	(0.492)	(0.087)	(0.272)	(0.089)	(0.181)	(0.038)	(0.070)
	[N=25,256]	[25,382]	[25,389]	[22,309]	[22,260]	[20,013]	[22,239]	[22,260]
Baseline mean	11.4	40.7	3.3	20.2	5.0	10.8	1.4	3.4
Competitive, Nonprofit	-0.063	1.237*	-0.002	-0.225	-0.008	-0.620*	-0.038	0.071
	(0.278)	(0.662)	(0.155)	(0.400)	(0.148)	(0.318)	(0.080)	(0.172)
	[N=7,203]	[7,266]	[7,266]	[6,832]	[6,762]	[6,069]	[6,762]	[6,762]
Baseline mean	13.8	32.2	2.8	21.6	4.8	11.0	1.1	3.7
Concentrated, For-Profit	-0.041	0.941	0.062	0.502	0.146	-0.099	0.083	0.070
	(0.349)	(0.989)	(0.179)	(0.442)	(0.157)	(0.374)	(0.094)	(0.143)
	[N=20,048]	[20,076]	[20,069]	[20,307]	[20,251]	[14,140]	[20,258]	[20,258]
Baseline mean	15.0	39.9	2.4	22.4	4.6	10.8	1.1	3.6
Concentrated, Nonprofit	0.050	-1.007	0.227	0.636	-0.072	-0.657*	0.017	0.005
	(0.519)	(0.854)	(0.142)	(0.798)	(0.311)	(0.378)	(0.141)	(0.180)
	[N=7,476]	[7,462]	[7,490]	[7,735]	[7,644]	[5,292]	[7,623]	[7,658]
Baseline mean	18.0	32.2	2.3	22.7	3.7	10.5	0.9	3.3
Panel B. Chain vs. Independent								
Competitive, Chain	0.040	0.245	0.046	-0.157	-0.086	-0.165	-0.016	0.074
	(0.159)	(0.609)	(0.108)	(0.282)	(0.108)	(0.208)	(0.068)	(0.113)
	[N=15,526]	[15,568]	[15,582]	[14,504]	[14,483]	[12,586]	[14,483]	[14,483]
Baseline mean	11.8	37.8	3.3	20.9	5.2	10.8	1.5	3.7
Competitive, Independent	-0.294	1.079	0.064	-0.431	-0.015	-0.439	-0.051	0.074
	(0.279)	(0.824)	(0.134)	(0.461)	(0.150)	(0.321)	(0.072)	(0.146)
	[N=10,059]	[10,157]	[10,150]	[9,226]	[9,149]	[8,183]	[9,135]	[9,149]
Baseline mean	12.4	39.1	3.0	20.2	4.6	10.8	1.1	3.3
Concentrated, Chain	0.207	0.284	0.035	0.479	0.229	-0.156	0.068	-0.087
	(0.455)	(1.054)	(0.280)	(0.576)	(0.193)	(0.621)	(0.092)	(0.189)
	[N=14,140]	[14,175]	[14,168]	[14,763]	[14,728]	[10,024]	[14,728]	[14,728]
Baseline mean	15.5	37.9	2.6	22.9	4.6	10.9	1.1	3.5
Concentrated, Independent	0.061	-0.926	0.165	1.332**	0.141	0.073	0.065	-0.021
	(0.498)	(2.152)	(0.167)	(0.574)	(0.203)	(0.318)	(0.116)	(0.176)
	[N=8,764]	[8,764]	[8,778]	[9,380]	[9,275]	[6,307]	[9,247]	[9,303]
Baseline mean	16.7	36.5	2.0	22.0	4.0	10.5	0.9	3.4
Panel C. High vs. Low Medicaid Share								
Competitive, High Medicaid	-0.397	-0.347	-0.006	0.214	0.086	-0.284	0.013	0.043
	(0.267)	(1.219)	(0.179)	(0.573)	(0.159)	(0.376)	(0.090)	(0.119)
	[N=5,418]	[5,523]	[5,537]	[5,110]	[5,047]	[3,486]	[5,040]	[5,054]
Baseline mean	11.7	46.4	3.2	18.2	3.8	9.2	1.1	2.2
Competitive, Low Medicaid	-0.202	0.245	0.076	-0.381	-0.089	-0.042	-0.059	0.049
	(0.179)	(0.403)	(0.092)	(0.253)	(0.116)	(0.241)	(0.053)	(0.099)
	[N=14,259]	[14,308]	[14,308]	[13,391]	[13,363]	[12,831]	[13,356]	[13,356]
Baseline mean	12.2	33.7	3.1	21.9	5.5	11.7	1.4	4.3
Concentrated, High Medicaid	-0.308	0.428	0.155	1.494**	0.644*	-0.038	-0.026	-0.002
	(0.870)	(1.517)	(0.508)	(0.760)	(0.355)	(0.838)	(0.168)	(0.249)
	[N=4,284]	[4,305]	[4,312]	[4,844]	[4,781]	[2,569]	[4,795]	[4,795]
Baseline mean	14.9	41.8	2.4	21.1	3.8	9.9	1.1	3.0
Concentrated, Low Medicaid	-0.169	-0.608	0.149	0.618	-0.144	-0.453	0.120	0.016
	(0.360)	(0.834)	(0.188)	(0.679)	(0.244)	(0.452)	(0.096)	(0.157)
	[N=12,796]	[12,817]	[12,817]	[13,335]	[13,300]	[9,457]	[13,286]	[13,307]
Baseline mean	16.5	35.3	2.3	23.2	4.6	11.1	1.0	3.7

Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

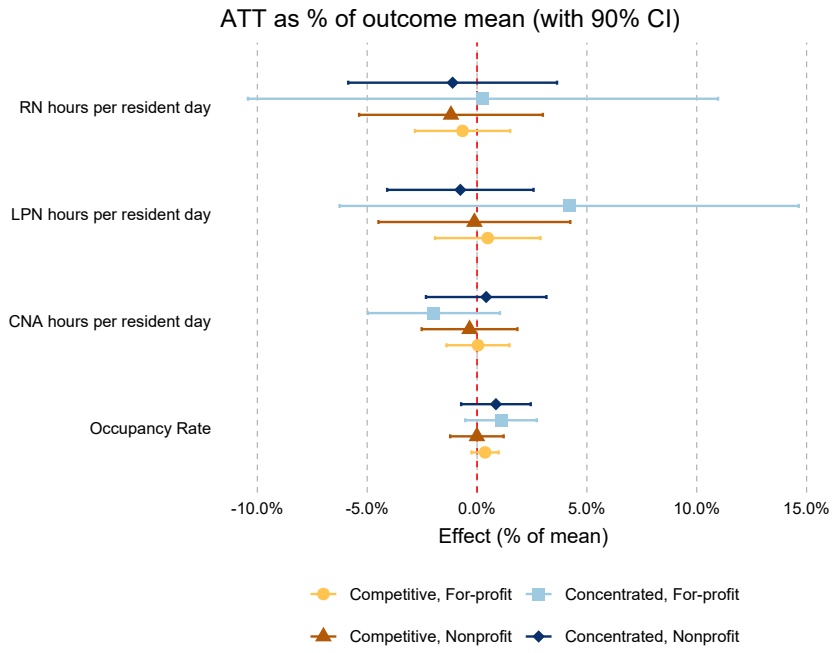
Table 4: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (by Ownership, Chain, and Medicaid Share; continued)

	Other Fracture (I4000)	Alzheimers (I4200)	Stroke (I4500)	Dementia (I4800)	Anxiety Disorder (I5700)	Depression (I5800)	Asthma/COPD (I6200)	Respiratory Failure (I6300)
Panel A. Profit vs. Nonprofit								
Competitive, For-Profit	0.101	0.385	-0.156	-0.640*	0.171	-0.351	0.016	0.170
	(0.105)	(0.236)	(0.288)	(0.366)	(0.354)	(0.418)	(0.227)	(0.151)
	[N=22,260]	[25,375]	[22,288]	[22,330]	[25,165]	[22,330]	[22,316]	[22,239]
Baseline mean	5.2	12.1	16.8	38.0	23.8	46.6	22.7	3.2
Competitive, Nonprofit	-0.161	-0.070	-0.831	-1.860**	-0.326	-0.570	-0.411	-0.039
	(0.250)	(0.452)	(0.534)	(0.821)	(0.474)	(0.665)	(0.412)	(0.170)
	[N=6,783]	[7,238]	[6,804]	[6,832]	[7,154]	[6,839]	[6,832]	[6,769]
Baseline mean	5.7	13.8	14.4	39.1	22.2	45.0	21.0	2.2
Concentrated, For-Profit	-0.042	0.694	-0.046	1.273	0.555	1.139*	1.108**	0.475**
	(0.220)	(0.433)	(0.459)	(0.854)	(0.563)	(0.621)	(0.437)	(0.207)
	[N=20,265]	[20,055]	[20,307]	[20,314]	[19,831]	[20,314]	[20,300]	[20,251]
Baseline mean	5.1	13.7	15.2	38.0	28.6	49.7	22.7	1.9
Concentrated, Nonprofit	-0.016	0.423	-0.623	-0.185	-0.223	-0.293	0.127	-0.399
	(0.292)	(0.538)	(0.718)	(1.003)	(0.916)	(0.696)	(0.514)	(0.359)
	[N=7,651]	[7,462]	[7,721]	[7,749]	[7,308]	[7,749]	[7,742]	[7,623]
Baseline mean	5.2	14.1	12.9	39.8	25.8	47.9	21.1	1.5
Panel B. Chain vs. Independent								
Competitive, Chain	0.028	0.305	-0.044	-0.892	0.147	-0.320	-0.053	0.377*
	(0.165)	(0.311)	(0.367)	(0.608)	(0.430)	(0.470)	(0.294)	(0.212)
	[N=14,483]	[15,568]	[14,490]	[14,518]	[15,470]	[14,518]	[14,518]	[14,483]
Baseline mean	5.8	12.2	16.6	37.2	24.1	46.9	22.6	3.1
Competitive, Independent	0.045	-0.048	-0.548	-0.901	-0.441	-0.626	-0.066	0.009
	(0.191)	(0.426)	(0.461)	(0.935)	(0.561)	(0.626)	(0.335)	(0.189)
	[N=9,163]	[10,129]	[9,191]	[9,226]	[9,989]	[9,233]	[9,219]	[9,142]
Baseline mean	4.8	13.0	15.7	39.7	22.5	45.2	21.7	2.6
Concentrated, Chain	0.175	0.061	-0.358	-0.507	0.670	0.209	1.088	0.164
	(0.260)	(0.551)	(0.700)	(0.840)	(0.840)	(0.809)	(0.671)	(0.303)
	[N=14,728]	[14,154]	[14,756]	[14,763]	[14,084]	[14,763]	[14,763]	[14,728]
Baseline mean	5.2	13.6	15.0	38.6	28.0	50.3	22.7	2.0
Concentrated, Independent	-0.284	0.646	-0.235	1.124	-0.240	0.476	0.210	0.139
	(0.221)	(0.455)	(0.521)	(0.800)	(0.816)	(0.623)	(0.417)	(0.255)
	[N=9,282]	[8,764]	[9,366]	[9,401]	[8,603]	[9,401]	[9,380]	[9,247]
Baseline mean	5.0	14.2	13.8	38.6	27.2	47.6	21.5	1.5
Panel C. High vs. Low Medicaid Share								
Competitive, High Medicaid	0.091	0.776	0.023	0.208	0.050	-0.270	0.025	0.093
	(0.197)	(0.498)	(0.749)	(0.917)	(0.776)	(0.870)	(0.612)	(0.352)
	[N=5,047]	[5,495]	[5,096]	[5,103]	[5,418]	[5,110]	[5,110]	[5,047]
Baseline mean	3.7	13.3	17.4	41.2	23.7	47.0	22.5	3.3
Competitive, Low Medicaid	0.115	-0.370	-0.087	-0.787*	-0.152	-0.837**	-0.341	0.046
	(0.125)	(0.316)	(0.328)	(0.476)	(0.304)	(0.424)	(0.253)	(0.146)
	[N=13,370]	[14,315]	[13,377]	[13,405]	[14,231]	[13,405]	[13,384]	[13,349]
Baseline mean	6.3	12.1	15.4	36.6	23.2	45.7	22.1	2.7
Concentrated, High Medicaid	0.404	1.851*	-0.135	2.968*	1.560	1.618	1.463*	0.706
	(0.343)	(1.124)	(1.281)	(1.720)	(1.453)	(1.352)	(0.839)	(0.458)
	[N=4,788]	[4,305]	[4,844]	[4,858]	[4,263]	[4,858]	[4,851]	[4,774]
Baseline mean	4.3	15.2	16.2	40.5	29.3	50.7	23.9	2.2
Concentrated, Low Medicaid	-0.223	0.420	-0.273	0.516	0.559	0.270	0.984*	0.368
	(0.204)	(0.592)	(0.732)	(0.784)	(0.788)	(0.968)	(0.534)	(0.300)
	[N=13,307]	[12,810]	[13,328]	[13,342]	[12,621]	[13,342]	[13,335]	[13,293]
Baseline mean	5.5	13.3	13.7	37.8	26.9	48.5	21.4	1.6

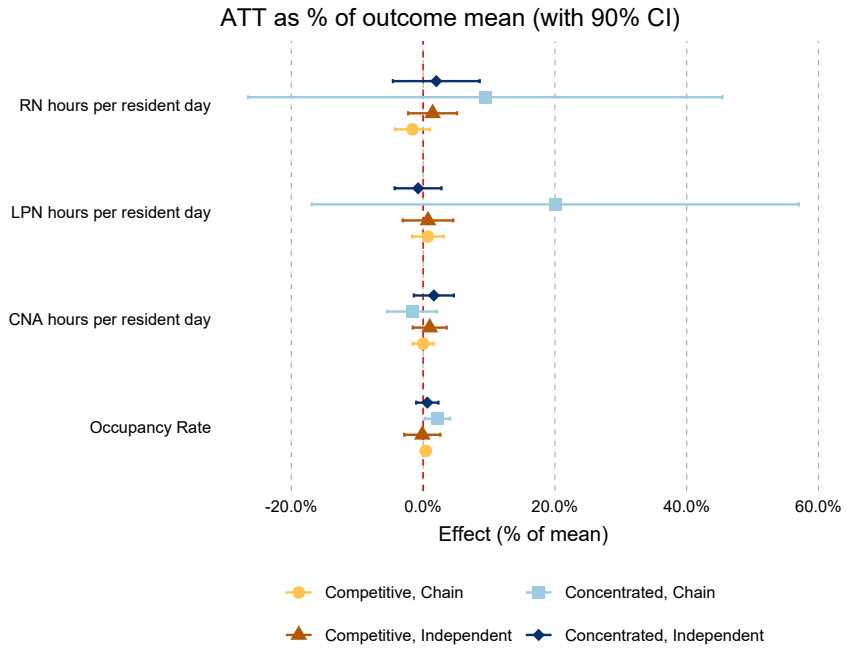
Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

Figure 6: Effects of Nursing Home Closures on Occupancy and Staffing (by Ownership, Chain, and Medicaid Share)

(a) By Ownership Type



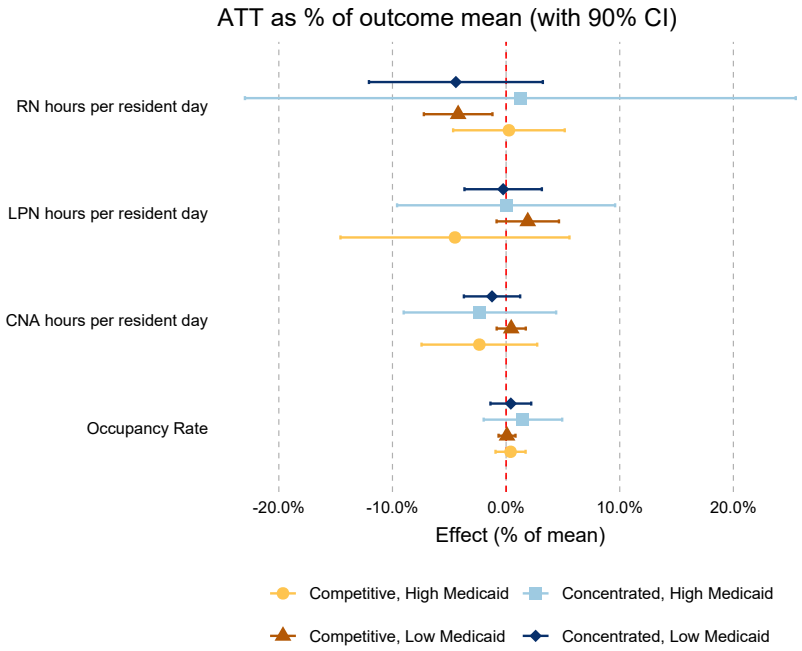
(b) By Chain Affiliation



Notes: Each panel displays coefficients from separate regressions in Table 5. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Figure 6: Effects of Nursing Home Closures on Occupancy and Staffing (by Ownership, Chain, and Medicaid Share; continued)

(c) By Medicaid Share



Notes: Each panel displays coefficients from separate regressions in Table 5. Capped lines indicate 90% confidence intervals. All effects are expressed as percentages of the outcome mean in the pre-closure period.

Table 5: Effects of Nursing Home Closures on Occupancy and Staffing (by Ownership, Chain, and Medicaid Share)

	Occupancy Rate	CNA HPRD	LPN HPRD	RN HPRD
Panel A. Profit vs. Nonprofit				
Competitive, For-Profit	0.302	0.001	0.004	-0.003
	(0.311)	(0.020)	(0.012)	(0.006)
	[N=25,739]	[26,789]	[26,523]	[26,355]
Baseline mean	82.7	2.3	0.8	0.5
Competitive, Nonprofit	-0.005	-0.009	-0.001	-0.007
	(0.645)	(0.035)	(0.022)	(0.015)
	[N=7,371]	[7,581]	[7,595]	[7,497]
Baseline mean	87.2	2.6	0.8	0.6
Concentrated, For-Profit	0.851	-0.043	0.033	0.001
	(0.771)	(0.040)	(0.050)	(0.024)
	[N=20,286]	[20,944]	[21,000]	[20,755]
Baseline mean	77.9	2.2	0.8	0.4
Concentrated, Nonprofit	0.743	0.010	-0.006	-0.005
	(0.832)	(0.040)	(0.016)	(0.013)
	[N=7,546]	[7,770]	[7,749]	[7,700]
Baseline mean	86.4	2.4	0.8	0.5
Panel B. Chain vs. Independent				
Competitive, Chain	0.338	0.000	0.006	-0.008
	(0.392)	(0.022)	(0.012)	(0.008)
	[N=15,729]	[16,254]	[16,149]	[15,995]
Baseline mean	82.5	2.3	0.8	0.5
Competitive, Independent	-0.102	0.025	0.006	0.007
	(1.420)	(0.039)	(0.019)	(0.011)
	[N=10,339]	[10,745]	[10,647]	[10,570]
Baseline mean	85.5	2.5	0.8	0.5
Concentrated, Chain	1.754*	-0.037	0.158	0.037
	(0.911)	(0.050)	(0.177)	(0.086)
	[N=14,266]	[14,700]	[14,735]	[14,616]
Baseline mean	79.7	2.2	0.8	0.4
Concentrated, Independent	0.522	0.038	-0.006	0.008
	(0.840)	(0.043)	(0.017)	(0.016)
	[N=8,918]	[9,149]	[9,149]	[9,093]
Baseline mean	82.1	2.3	0.8	0.4
Panel C. High vs. Low Medicaid Share				
Competitive, High Medicaid	0.328	-0.054	-0.036	0.001
	(0.672)	(0.071)	(0.049)	(0.012)
	[N=5,642]	[5,845]	[5,789]	[5,782]
Baseline mean	83.5	2.3	0.8	0.4
Competitive, Low Medicaid	0.068	0.011	0.016	-0.023**
	(0.380)	(0.019)	(0.014)	(0.010)
	[N=14,448]	[14,896]	[14,889]	[14,728]
Baseline mean	84.1	2.4	0.8	0.5
Concentrated, High Medicaid	1.163	-0.052	0.000	0.004
	(1.649)	(0.092)	(0.048)	(0.047)
	[N=4,347]	[4,494]	[4,522]	[4,480]
Baseline mean	78.5	2.3	0.8	0.3
Concentrated, Low Medicaid	0.340	-0.028	-0.002	-0.019
	(0.891)	(0.034)	(0.016)	(0.020)
	[N=12,936]	[13,321]	[13,321]	[13,251]
Baseline mean	81.7	2.3	0.8	0.4

Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample means for each subsample.

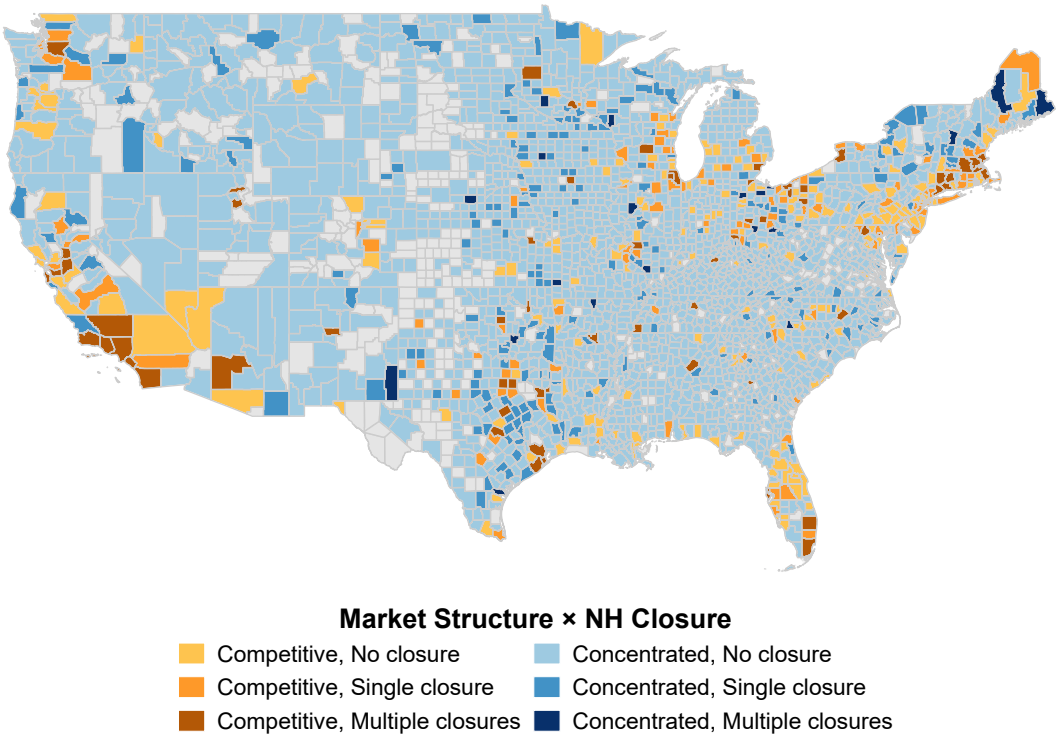
Appendix

Table A1: Summary of Data Sources

Data Source	**Spatial Unit**	**Time Span**	**Frequency**
Provider of Services (POS) File	Facility level	2011–2017	Quarterly
Minimum Data Set (MDS) 3.0	Individual level	2011–2017	Annual
Long-Term Care: Facts on Care in the U.S. (LTCFocus)	Facility level	2011–2017	Annual
Area Health Resources Files (AHRF)	County level	2011–2017	Annual

Notes: Frequency refers to the aggregation used in the analysis. MDS contains multiple assessments per year but is summarized annually; POS is processed quarterly.

Figure A1: Market Structure and Nursing Home (NH) Closures at the County Level



Note: Darker shades indicate a greater number of closures within each market type. Competitive markets are shown in orange tones and concentrated markets in blue tones.

Table A2: Market Structure by Urban–Rural Classification

Market Structure	Metropolitan	Micropolitan	Uncore	Total
Competitive	354 (12.93%)	20 (0.73%)	4 (0.15%)	378 (13.81%)
Concentrated	724 (26.43%)	575 (20.99%)	1,062 (38.77%)	2,361 (86.19%)
Total	1,078 (39.36%)	595 (21.72%)	1,066 (38.92%)	2,739 (100.00%)

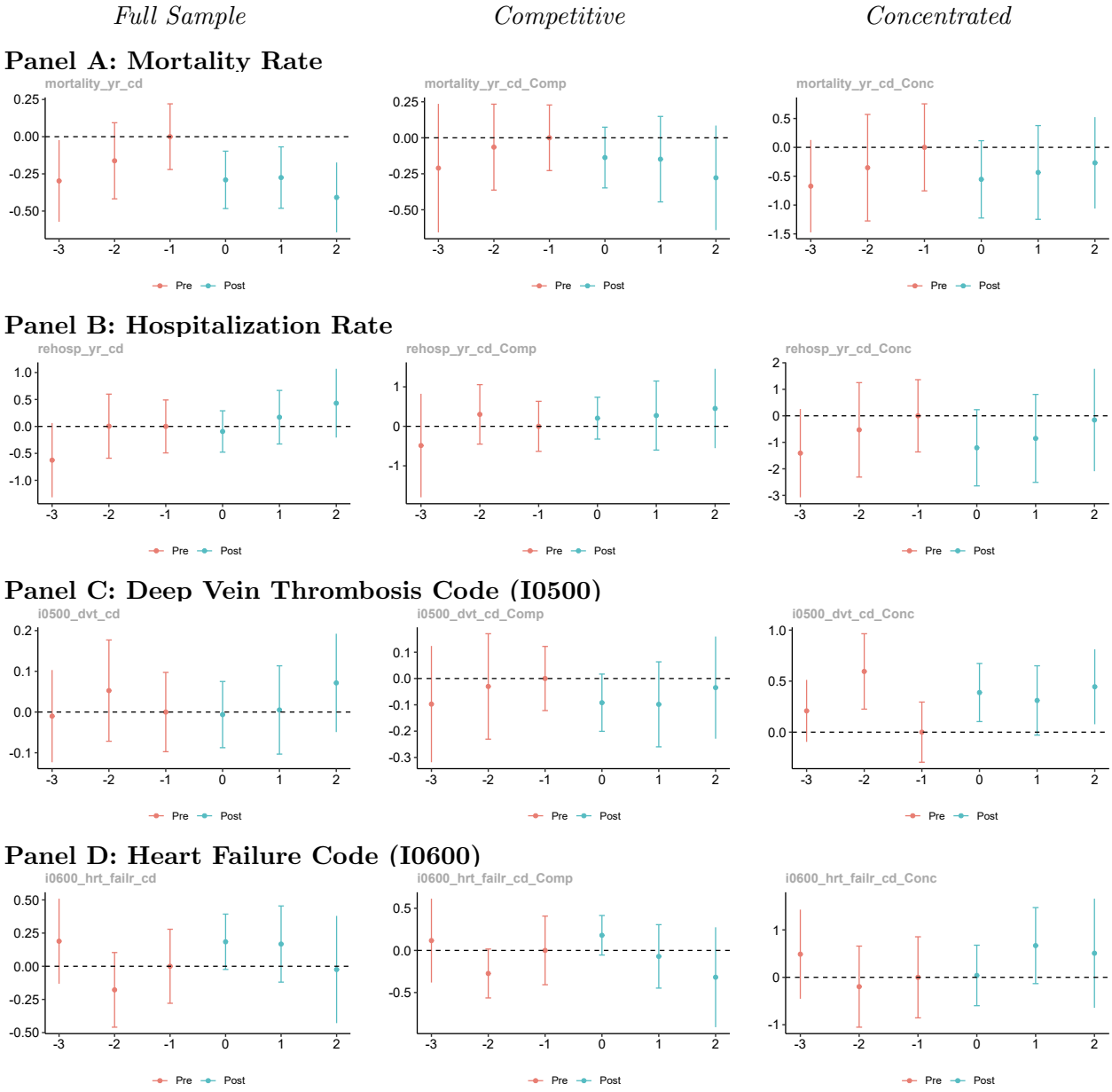
Note: Out of 2788 counties, 49 were excluded due to changes in market structure during the study period. Counties are classified according to the 2013 Urban Influence Codes (UIC) from the Economic Research Service, U.S. Department of Agriculture. Metropolitan counties correspond to UICs 1–2, micropolitan counties to UICs 3, 5, and 8, and uncore counties to UICs 4, 6, 7, and 9–12. Percentages represent column shares within each market structure.

Table A3: Variable Definitions for Health Outcomes

Variable	Label	Description
MORTALITY_RT	Mortality Rate	Constructed from annual resident-level discharge records. For each facility-year, I count the number of unique residents and calculate the share of discharges whose reason is recorded as deceased.
HOSPITILIZATION_RT	Hospitalization Rate	Constructed from annual resident-level discharge records. For each facility-year, I calculate the share of discharges whose reason is recorded as an acute hospital transfer.
I0500_DVT_CD	I0500 Active Diagnoses: Deep Vein Thrombosis (DVT) Code	The data in this column indicates whether the resident had a diagnosis of deep vein thrombosis, pulmonary embolus (PE), or pulmonary thrombo-embolism (PTE) in the last seven days.
I0600_HRT_FAILR_CD	I0600 Active Diagnoses: Heart Failure (CHF) Code	Indicates whether the resident had a diagnosis of heart failure (e.g., congestive heart failure [CHF] or pulmonary edema) in the last seven days.
I2000_PNEUMO_CD	I2000 Active Diagnoses: Pneumonia Code	Indicates whether the resident had an active diagnosis of pneumonia in the last seven days.
I2300_UTI_CD	I2300 Active Diagnoses: Urinary Tract Infection (UTI) Code	Indicates whether the resident had an active diagnosis of urinary tract infection (UTI) in the last 30 days.
I2500_WND_INFCTN_CD	I2500 Wound Infection Code	Indicates whether the resident had an active diagnosis of a wound infection (other than foot) in the last seven days.
I3900_HIP_FRCTR_CD	I3900 Active Diagnoses: Hip Fracture Code	Indicates whether the resident had an active diagnosis of any hip fracture that is related to current status, treatments, or monitoring (e.g., sub-capital fractures, and fractures of the trochanter and femoral neck) in the last seven days.
I4000_OTHR_FRCTR_CD	I4000 Active Diagnoses: Other Fracture Code	Indicates whether the resident had an active diagnosis of other fractures in the last seven days.
I4200_ALZHMR_CD	I4200 Active Diagnoses: Alzheimer's Disease Code	Indicates whether the resident had an active diagnosis of Alzheimer's Disease in the last seven days.
I4500_STRK_CD	I4500 Active Diagnoses: Stroke (CVA or TIA or Stroke) Code	Indicates whether the resident had an active diagnosis of cerebrovascular accident (CVA), transient ischemic attack (TIA), or stroke in the last seven days.
I4800_DMNT_CD	I4800 Active Diagnoses: Dementia Code	Indicates whether the resident had an active diagnosis of dementia (e.g., Lewy body, vascular or multi-infarct, mixed, fronto-temporal such as Pick's Disease, or dementia related to stroke, Parkinson's Disease, or Creutzfeldt-Jakob Disease) in the last seven days.
I5700_ANXTY_DSORDR_CD	I5700 Active Diagnoses: Anxiety Disorder Code	Indicates whether the resident had an active diagnosis of an anxiety disorder in the last seven days.
I5800_DPRSN_CD	I5800 Active Diagnoses: Depression Code	Indicates whether the resident had an active diagnosis of depression (other than bipolar) in the last seven days.
I6200_ASTHMA_CD	I6200 Active Diagnoses: Asthma, COPD, or Chronic Lung Disease Code	Indicates whether the resident had an active diagnosis of asthma, chronic obstructive pulmonary disease (COPD), or chronic lung disease (e.g., chronic bronchitis or restrictive lung disease such as asbestosis) in the last seven days.
I6300_RSPRTRY_FAILR_CD	I6300 Active Diagnoses: Respiratory Failure Code	Indicates whether the resident had an active diagnosis of respiratory failure in the last seven days.

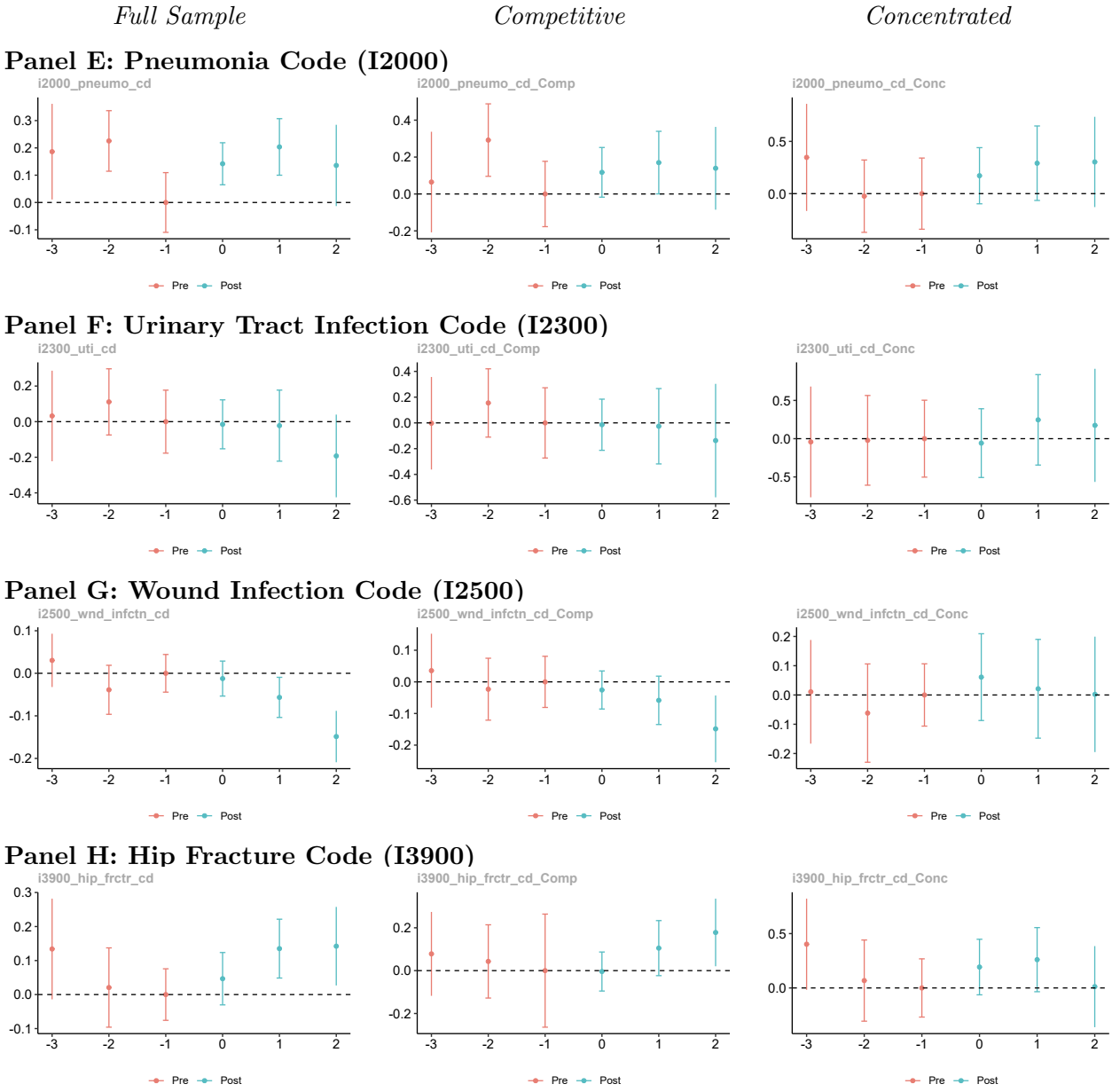
Notes: Variable definitions are based on the Minimum Data Set (MDS) resident-level assessments. All active diagnoses indicators are coded as binary variables equal to one if the condition was active during the specified reference period.

Figure A2: Event-Study Estimates for Mortality, Hospitalization, and Active Diagnoses



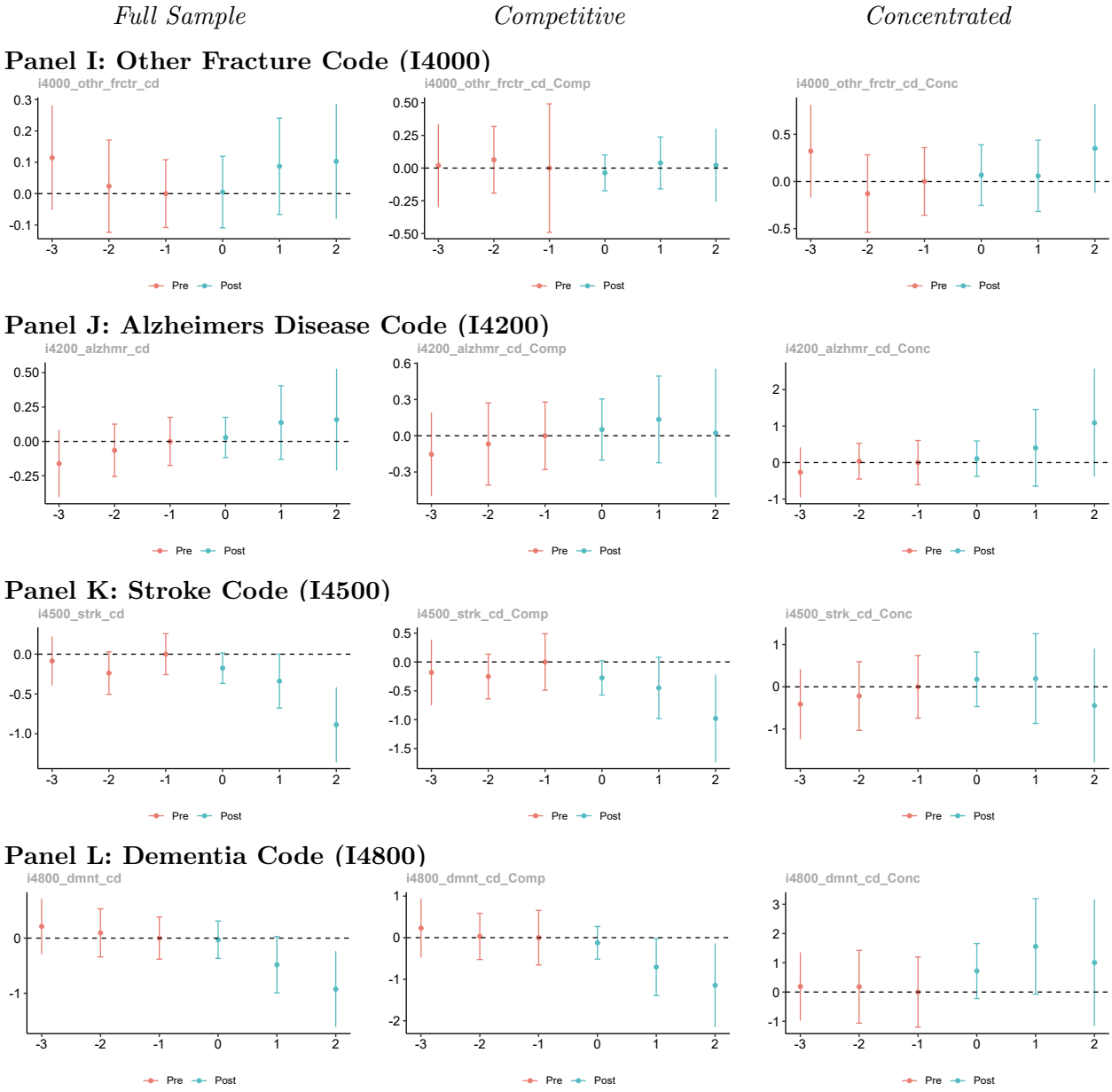
Notes: Each panel reports event-study estimates for a distinct outcome. Columns correspond to full sample, competitive markets, and concentrated markets. Estimates are based on the specification with covariates and without matched samples. Confidence bands represent 90% intervals from the main specification.

Figure A2: Event-Study Estimates for Mortality, Hospitalization, and Active Diagnoses (continued)



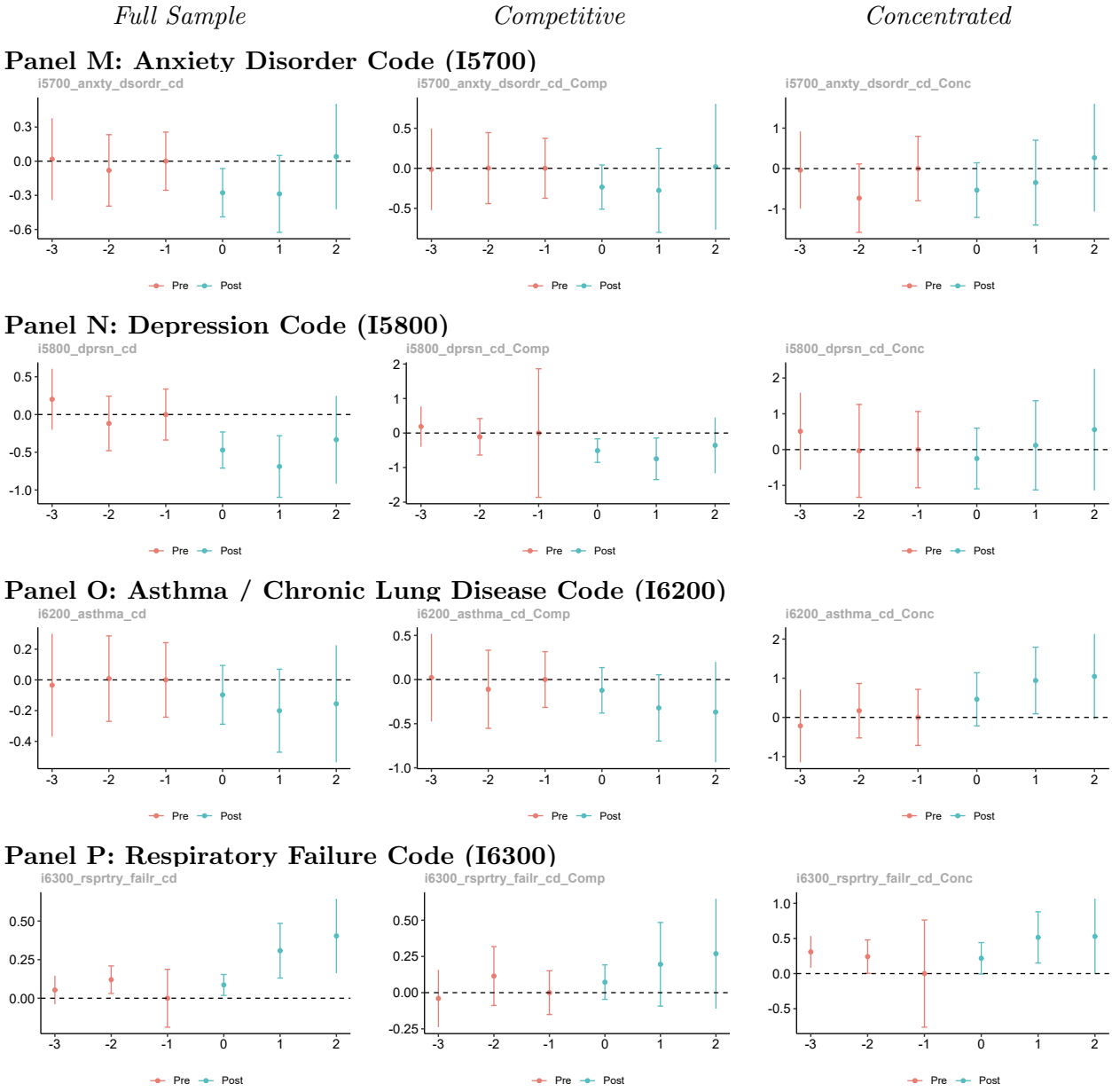
Notes: Each panel reports event-study estimates for a distinct outcome. Columns correspond to full sample, competitive markets, and concentrated markets. Estimates are based on the specification with covariates and without matched samples. Confidence bands represent 90% intervals from the main specification.

Figure A2: Event-Study Estimates for Mortality, Hospitalization, and Active Diagnoses (continued)



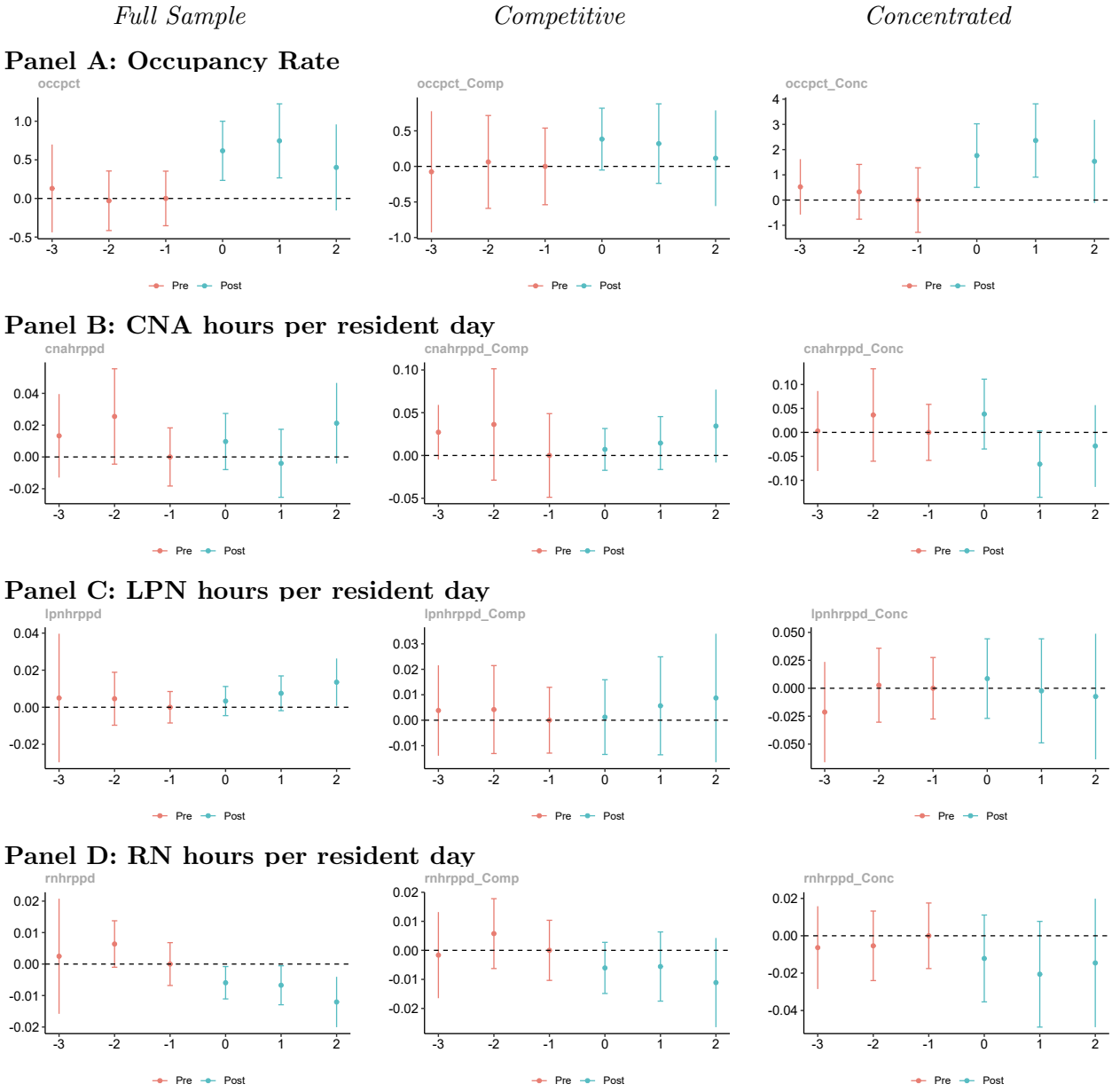
Notes: Each panel reports event-study estimates for a distinct outcome. Columns correspond to full sample, competitive markets, and concentrated markets. Estimates are based on the specification with covariates and without matched samples. Confidence bands represent 90% intervals from the main specification.

Figure A2: Event-Study Estimates for Active Diagnoses (continued)



Notes: Each panel reports event-study estimates for a distinct outcome. Columns correspond to full sample, competitive markets, and concentrated markets. Estimates are based on the specification with covariates and without matched samples. Confidence bands represent 90% intervals from the main specification.

Figure A3: Event-Study Estimates for Occupancy and Staffing



Notes: Each panel reports event-study estimates for a distinct outcome. Columns correspond to full sample, competitive markets, and concentrated markets. Estimates are based on the specification with covariates and without matched samples. Confidence bands represent 90% intervals from the main specification.

Table A4: Descriptive Statistics (Single-closure Counties): Treated vs. Control and Matched Control (2011)

Variable	Treated			Control			Matched Control		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Facility-level characteristics									
Occupancy rate (%)	1,465	85.17	13.40	6,440	83.01	14.15	1,553	85.27	12.53
Total beds	1,468	120.18	74.59	6,447	103.90	54.93	1,557	115.22	64.52
For-profit ownership (1=yes)	1,468	0.68	0.47	6,447	0.69	0.46	1,557	0.68	0.47
Multi-facility affiliation (1=yes)	1,468	0.49	0.50	6,447	0.58	0.49	1,557	0.56	0.50
Hospital-based (1=yes)	1,468	0.03	0.18	6,447	0.05	0.21	1,557	0.03	0.18
Average resident age	1,463	80.99	6.40	6,415	81.04	5.51	1,550	81.11	6.04
Female residents (%)	1,452	70.12	11.74	6,361	70.18	10.40	1,535	70.14	11.02
White residents (%)	1,450	84.31	22.44	6,376	85.94	19.25	1,537	83.35	20.68
Medicaid residents (%)	1,468	62.83	18.30	6,447	63.08	17.58	1,557	60.76	19.07
Medicare residents (%)	1,468	14.10	10.74	6,447	13.72	10.78	1,557	14.64	11.70
Acuity index	1,468	11.81	1.55	6,447	11.84	1.62	1,557	11.92	1.56
CNA hours per resident day	1,467	2.34	0.58	6,443	2.33	0.65	1,557	2.37	0.63
LPN hours per resident day	1,467	0.76	0.31	6,445	0.81	0.48	1,557	0.81	0.33
RN hours per resident day	1,468	0.44	0.39	6,447	0.39	0.39	1,557	0.42	0.32
County-level characteristics									
Herfindahl–Hirschman Index (HHI)	1,487	0.14	0.13	6,471	0.35	0.28	1,558	0.17	0.14
Population	1,487	429,093	544,263	6,471	167,398	310,840	1,558	337,285	453,598
Population aged 65+ (%)	1,487	14.71	3.17	6,471	15.77	3.78	1,558	15.54	4.07
White population (%)	1,487	72.00	21.28	6,471	78.02	18.89	1,558	73.89	19.69
Dual-eligible share (%)	1,487	24.52	10.07	6,471	22.14	8.09	1,558	20.82	8.08
Median household income ($)	1,487	49,266	12,530	6,471	45,855	11,897	1,558	50,063	13,959
Number of counties		240			2,100			240	

Notes: Appendix table restricted to single-closure counties. Treated counties experienced exactly one nursing home closure by 2011; control counties had none. Matched controls are selected via county-level optimal propensity score matching. Variables are measured at the facility level unless otherwise noted. County characteristics are for 2011.

Table A5: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (Single-closure Counties)

	Mortality Rate	Hospitalization Rate	DVT (I0500)	Heart Failure (I0600)	Pneumonia (I2000)	UTI (I2300)	Wound Infection (I2500)	Hip Fracture (I3900)
Panel A. No controls (Single-closure)								
Full Sample	-0.005	0.000	-0.076	0.379**	0.030	-0.028	-0.003	0.066
	(0.137)	(0.358)	(0.070)	(0.184)	(0.067)	(0.117)	(0.031)	(0.059)
	[N=53,354]	[53,662]	[53,746]	[52,542]	[52,178]	[38,640]	[52,101]	[52,199]
Competitive	0.188	0.242	-0.138	-0.101	-0.031	0.189	0.030	0.059
	(0.183)	(0.707)	(0.133)	(0.294)	(0.099)	(0.251)	(0.049)	(0.094)
	[N=17,339]	[17,514]	[17,535]	[16,618]	[16,562]	[14,126]	[16,548]	[16,548]
Concentrated	-0.048	0.023	0.009	0.721**	0.136	-0.125	0.050	0.069
	(0.317)	(0.906)	(0.162)	(0.351)	(0.140)	(0.305)	(0.076)	(0.138)
	[N=29,960]	[30,072]	[30,121]	[29,974]	[29,764]	[20,566]	[29,715]	[29,792]
Panel B. With controls (Single-closure)								
Full Sample	-0.103	-0.112	-0.099	0.337*	0.029	-0.099	0.009	0.049
	(0.188)	(0.379)	(0.076)	(0.196)	(0.065)	(0.125)	(0.031)	(0.077)
	[N=48,559]	[48,692]	[48,699]	[48,097]	[47,810]	[35,490]	[47,761]	[47,845]
Competitive	0.182	0.166	-0.204	-0.109	-0.042	0.031	0.006	0.055
	(0.247)	(0.673)	(0.139)	(0.309)	(0.105)	(0.260)	(0.051)	(0.098)
	[N=15,813]	[15,911]	[15,904]	[15,253]	[15,197]	[12,999]	[15,190]	[15,190]
Concentrated	-0.058	-0.290	0.032	0.684*	0.053	-0.187	0.057	0.033
	(0.320)	(0.909)	(0.162)	(0.381)	(0.138)	(0.308)	(0.070)	(0.128)
	[N=27,419]	[27,433]	[27,461]	[27,524]	[27,342]	[19,019]	[27,307]	[27,370]
Panel C. With controls, matched sample (Single-closure)								
Full Sample	-0.039	-0.083	-0.147	0.123	-0.012	-0.116	0.050	0.055
	(0.260)	(0.755)	(0.125)	(0.377)	(0.121)	(0.237)	(0.060)	(0.108)
	[N=17,822]	[17,913]	[17,913]	[16,870]	[16,758]	[13,776]	[16,765]	[16,772]
Competitive	0.113	-0.076	-0.198	-0.088	0.012	0.030	0.008	0.073
	(0.271)	(0.727)	(0.161)	(0.334)	(0.107)	(0.298)	(0.065)	(0.112)
	[N=11,578]	[11,669]	[11,669]	[10,948]	[10,906]	[9,429]	[10,899]	[10,899]
Concentrated	-0.180	0.000	0.093	0.508	0.184	-0.336	0.050	-0.064
	(0.366)	(0.980)	(0.206)	(0.497)	(0.153)	(0.346)	(0.089)	(0.159)
	[N=5,985]	[5,999]	[5,999]	[5,775]	[5,726]	[4,032]	[5,733]	[5,740]
Baseline mean								
Full Sample	13.8	37.4	2.9	21.2	4.5	10.3	1.0	3.3
Competitive	12.7	37.4	3.0	20.7	4.6	10.1	1.0	3.2
Concentrated	16.6	37.0	2.2	22.7	4.4	10.7	1.0	3.5

Notes: Single-closure counties only. Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby nursing home closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample averages.

Table A5: Effects of Nursing Home Closures on Active Diagnoses (Single-closure Counties; continued)

	Other Fracture (I4000)	Alzheimers (I4200)	Stroke (I4500)	Dementia (I4800)	Anxiety Disorder (I5700)	Depression (I5800)	Asthma/COPD (I6200)	Respiratory Failure (I6300)
Panel A. No controls (Single-closure)								
Full Sample	0.060	0.138	0.141	-0.410	0.503**	-0.116	0.236	0.098
	(0.113)	(0.204)	(0.219)	(0.315)	(0.251)	(0.267)	(0.186)	(0.071)
	[N=52,220]	[53,557]	[52,444]	[52,605]	[52,682]	[52,619]	[52,556]	[52,115]
Competitive	0.032	-0.256	0.304	-0.604	0.612	-0.068	0.232	0.088
	(0.106)	(0.338)	(0.338)	(0.479)	(0.738)	(0.449)	(0.258)	(0.198)
	[N=16,576]	[17,465]	[16,590]	[16,632]	[17,192]	[16,639]	[16,632]	[16,548]
Concentrated	-0.067	0.964**	-0.024	0.785	0.378	0.140	0.503	0.191
	(0.186)	(0.388)	(0.445)	(0.601)	(0.521)	(0.479)	(0.351)	(0.169)
	[N=29,771]	[30,058]	[29,932]	[30,002]	[29,561]	[30,009]	[29,981]	[29,722]
Panel B. With controls (Single-closure)								
Full Sample	0.013	0.038	0.149	-0.431	0.304	-0.175	0.309*	0.110
	(0.114)	(0.178)	(0.242)	(0.331)	(0.263)	(0.266)	(0.184)	(0.078)
	[N=47,852]	[48,643]	[48,034]	[48,111]	[48,041]	[48,118]	[48,104]	[47,761]
Competitive	-0.047	-0.395	0.292	-0.690*	0.172	-0.317	0.338	0.104
	(0.130)	(0.351)	(0.314)	(0.383)	(0.708)	(0.431)	(0.298)	(0.213)
	[N=15,211]	[15,883]	[15,225]	[15,253]	[15,694]	[15,260]	[15,260]	[15,190]
Concentrated	-0.053	0.823**	-0.086	0.820	0.348	0.245	0.723**	0.219
	(0.170)	(0.400)	(0.477)	(0.688)	(0.499)	(0.522)	(0.344)	(0.171)
	[N=27,356]	[27,433]	[27,496]	[27,538]	[27,104]	[27,538]	[27,524]	[27,307]
Panel C. With controls, matched sample (Single-closure)								
Full Sample	0.053	-0.077	0.128	-0.687	0.308	-0.299	0.267	-0.001
	(0.201)	(0.337)	(0.412)	(0.599)	(0.486)	(0.517)	(0.363)	(0.148)
	[N=16,786]	[17,892]	[16,828]	[16,884]	[17,654]	[16,884]	[16,884]	[16,751]
Competitive	-0.023	-0.570	0.129	-0.509	0.269	-0.093	0.464	0.091
	(0.155)	(0.392)	(0.335)	(0.461)	(0.663)	(0.535)	(0.342)	(0.242)
	[N=10,913]	[11,641]	[10,934]	[10,948]	[11,494]	[10,955]	[10,962]	[10,899]
Concentrated	-0.119	0.849*	-0.293	0.776	0.668	0.490	0.557	0.274
	(0.213)	(0.521)	(0.594)	(0.785)	(0.613)	(0.642)	(0.433)	(0.206)
	[N=5,740]	[5,999]	[5,768]	[5,782]	[5,922]	[5,782]	[5,782]	[5,726]
Baseline mean								
Full Sample	5.0	12.8	15.1	39.6	24.5	46.1	22.4	2.5
Competitive	5.0	12.5	15.2	40.1	23.5	45.0	22.9	2.7
Concentrated	5.1	13.5	14.2	38.2	27.6	49.6	21.9	1.8

Notes: Continued from Table A5. Single-closure counties only. Each cell reports the coefficient from facility-level regressions of the corresponding diagnosis on exposure to nearby nursing home closures. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample averages.

Table A6: Effects of Nursing Home Closures on Occupancy and Staffing (Single-closure Counties)

	Occupancy Rate	CNA HPRD	LPN HPRD	RN HPRD
Panel A. No controls (Single-closure)				
Full Sample	0.743**	0.002	0.014**	-0.004
	(0.363)	(0.013)	(0.007)	(0.005)
	[N=53,767]	[53,228]	[53,032]	[52,605]
Competitive	-0.065	-0.003	0.004	0.003
	(0.420)	(0.021)	(0.013)	(0.008)
	[N=17,605]	[17,479]	[17,388]	[17,269]
Concentrated	1.696**	0.004	0.007	-0.006
	(0.743)	(0.027)	(0.013)	(0.011)
	[N=30,191]	[29,827]	[29,848]	[29,575]
Panel B. With controls (Single-closure)				
Full Sample	0.821**	-0.007	0.009	-0.002
	(0.370)	(0.013)	(0.006)	(0.004)
	[N=49,252]	[51,030]	[50,855]	[50,393]
Competitive	-0.024	-0.008	0.003	0.005
	(0.473)	(0.021)	(0.014)	(0.009)
	[N=16,107]	[16,688]	[16,590]	[16,450]
Concentrated	1.816***	0.008	0.012	0.000
	(0.659)	(0.026)	(0.019)	(0.013)
	[N=27,734]	[28,623]	[28,658]	[28,385]
Panel C. With controls, matched sample (Single-closure)				
Full Sample	1.022	-0.002	0.004	-0.002
	(0.637)	(0.024)	(0.012)	(0.009)
	[N=18,088]	[18,886]	[18,774]	[18,557]
Competitive	0.279	-0.005	0.005	0.008
	(0.439)	(0.025)	(0.014)	(0.010)
	[N=11,844]	[12,341]	[12,271]	[12,124]
Concentrated	2.113**	0.018	0.020	-0.009
	(0.845)	(0.033)	(0.014)	(0.014)
	[N=6,055]	[6,272]	[6,279]	[6,174]
Baseline mean				
Full Sample	84.8	2.4	0.7	0.5
Competitive	86.9	2.4	0.7	0.5
Concentrated	80.0	2.2	0.8	0.4

Notes: Single-closure counties only. Each cell reports the estimated effect of nearby nursing home closures on occupancy and staffing intensity. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. HPRD is hours per resident day. Baseline means are pre-closure sample averages.

Table A7: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (Radius Sensitivity)

	Mortality Rate	Hospitalization Rate	DVT (I0500)	Heart Failure (I0600)	Pneumonia (I2000)	UTI (I2300)	Wound Infection (I2500)	Hip Fracture (I3900)
Panel A. 15-mile radius								
Full Sample	-0.122*	0.057	0.172***	-0.063	-0.039	-0.588***	-0.077***	0.104**
	(0.073)	(0.224)	(0.055)	(0.132)	(0.051)	(0.097)	(0.029)	(0.044)
	[N=72,737]	[72,954]	[72,996]	[66,381]	[66,024]	[53,977]	[65,947]	[66,059]
Baseline mean	12.8	37.9	3.0	21.4	4.9	11.1	1.3	3.7
Competitive	-0.028	-0.184	0.235***	-0.291*	-0.047	-0.510***	-0.044	0.129**
	(0.087)	(0.281)	(0.064)	(0.157)	(0.067)	(0.116)	(0.031)	(0.051)
	[N=35,238]	[35,392]	[35,413]	[29,463]	[29,344]	[28,049]	[29,316]	[29,337]
Baseline mean	12.0	38.0	3.2	21.0	5.1	11.2	1.4	3.7
Concentrated	-0.157	0.000	0.056	0.164	0.076	-0.516**	-0.061	0.067
	(0.183)	(0.457)	(0.089)	(0.302)	(0.102)	(0.203)	(0.051)	(0.094)
	[N=30,912]	[30,947]	[30,982]	[30,786]	[30,597]	[21,553]	[30,562]	[30,625]
Baseline mean	15.3	37.6	2.5	22.3	4.4	10.9	1.1	3.6
Panel B. 10-mile radius								
Full Sample	-0.233**	-0.267	0.083	0.097	-0.041	-0.610***	-0.108***	0.068
	(0.098)	(0.308)	(0.052)	(0.139)	(0.065)	(0.107)	(0.031)	(0.046)
	[N=77,133]	[77,427]	[77,469]	[73,206]	[72,842]	[57,414]	[72,765]	[72,877]
Baseline mean	12.1	38.9	3.2	20.6	4.8	11.0	1.3	3.6
Competitive	-0.124	-0.238	0.119*	-0.154	0.017	-0.458***	-0.071**	0.105**
	(0.085)	(0.276)	(0.063)	(0.162)	(0.066)	(0.114)	(0.030)	(0.052)
	[N=39,102]	[39,333]	[39,354]	[35,336]	[35,210]	[31,101]	[35,182]	[35,203]
Baseline mean	11.6	39.2	3.3	20.4	4.9	10.9	1.3	3.5
Concentrated	0.006	0.096	-0.046	0.661*	-0.049	-0.712**	-0.025	-0.105
	(0.216)	(0.550)	(0.111)	(0.363)	(0.112)	(0.287)	(0.064)	(0.114)
	[N=31,388]	[31,423]	[31,458]	[31,647]	[31,458]	[21,910]	[31,423]	[31,486]
Baseline mean	14.8	37.4	2.6	21.7	4.5	11.1	1.2	3.7
Panel C. 5-mile radius								
Full Sample	-0.223**	-0.323	0.130*	0.176	0.048	-0.353**	-0.040	0.068
	(0.097)	(0.344)	(0.067)	(0.171)	(0.076)	(0.137)	(0.034)	(0.058)
	[N=81,004]	[81,347]	[81,389]	[79,968]	[79,597]	[60,529]	[79,513]	[79,625]
Baseline mean	12.0	39.4	3.3	20.5	4.7	10.6	1.3	3.5
Competitive	-0.179*	-0.332	0.137*	-0.058	0.046	-0.210	-0.028	0.069
	(0.106)	(0.364)	(0.080)	(0.179)	(0.089)	(0.142)	(0.038)	(0.062)
	[N=42,693]	[42,973]	[42,994]	[41,489]	[41,356]	[33,978]	[41,321]	[41,342]
Baseline mean	11.4	39.7	3.4	20.2	4.8	10.6	1.3	3.4
Concentrated	0.035	-0.284	-0.018	0.760*	0.125	-0.694*	0.062	0.087
	(0.270)	(0.725)	(0.157)	(0.400)	(0.137)	(0.371)	(0.090)	(0.155)
	[N=31,640]	[31,675]	[31,710]	[32,172]	[31,983]	[22,120]	[31,948]	[32,011]
Baseline mean	15.1	38.7	2.6	22.3	4.4	10.9	1.1	3.8

Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby nursing home closures within the specified radius. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample averages.

Table A7: Effects of Nursing Home Closures on Mortality, Hospitalization, and Active Diagnoses (Radius Sensitivity; continued)

	Other Fracture (I4000)	Alzheimers (I4200)	Stroke (I4500)	Dementia (I4800)	Anxiety Disorder (I5700)	Depression (I5800)	Asthma/COPD (I6200)	Respiratory Failure (I6300)
Panel A. 15-mile radius								
Full Sample	0.030	0.185*	0.174*	-0.324	0.429**	-0.119	0.206	0.092
	(0.112)	(0.110)	(0.102)	(0.217)	(0.180)	(0.191)	(0.143)	(0.065)
	[N=65,954]	[66,155]	[65,968]	[66,012]	[66,030]	[66,014]	[65,981]	[65,925]
Baseline mean	5.0	12.9	15.2	39.6	24.5	46.1	22.4	2.5
Competitive	0.023	-0.229	0.262	-0.552	0.533	-0.080	0.254	0.094
	(0.108)	(0.228)	(0.223)	(0.404)	(0.310)	(0.281)	(0.235)	(0.110)
	[N=29,348]	[29,465]	[29,352]	[29,356]	[29,364]	[29,359]	[29,357]	[29,342]
Baseline mean	5.0	12.6	15.1	39.9	23.6	44.8	22.7	2.8
Concentrated	-0.061	0.897***	-0.023	0.794	0.364	0.120	0.485	0.173
	(0.192)	(0.340)	(0.319)	(0.501)	(0.429)	(0.393)	(0.292)	(0.143)
	[N=30,582]	[30,694]	[30,673]	[30,682]	[30,674]	[30,677]	[30,663]	[30,626]
Baseline mean	5.1	13.5	14.2	38.4	27.7	49.6	21.9	1.7
Panel B. 10-mile radius								
Full Sample	0.045	0.151	0.178	-0.366	0.379**	-0.145	0.246	0.096
	(0.116)	(0.135)	(0.126)	(0.238)	(0.198)	(0.208)	(0.157)	(0.071)
	[N=72,773]	[72,974]	[72,792]	[72,816]	[72,824]	[72,819]	[72,793]	[72,755]
Baseline mean	5.1	12.8	15.1	39.5	24.4	46.0	22.4	2.5
Competitive	0.018	-0.265	0.293	-0.614	0.561	-0.083	0.272	0.099
	(0.111)	(0.249)	(0.236)	(0.422)	(0.328)	(0.297)	(0.254)	(0.120)
	[N=35,188]	[35,305]	[35,196]	[35,202]	[35,210]	[35,205]	[35,196]	[35,182]
Baseline mean	5.1	12.5	15.0	39.8	23.5	44.9	22.7	2.8
Concentrated	-0.058	0.876***	-0.021	0.805	0.358	0.131	0.506	0.186
	(0.198)	(0.352)	(0.334)	(0.516)	(0.437)	(0.407)	(0.301)	(0.155)
	[N=31,453]	[31,565]	[31,544]	[31,553]	[31,545]	[31,548]	[31,534]	[31,497]
Baseline mean	5.2	13.4	14.1	38.3	27.6	49.5	21.9	1.7
Panel C. 5-mile radius								
Full Sample	0.061	0.120	0.168	-0.401	0.341**	-0.166	0.267	0.091
	(0.121)	(0.144)	(0.138)	(0.252)	(0.209)	(0.220)	(0.164)	(0.073)
	[N=79,582]	[79,783]	[79,601]	[79,625]	[79,633]	[79,628]	[79,602]	[79,564]
Baseline mean	5.0	12.8	15.1	39.6	24.5	46.1	22.4	2.5
Competitive	0.028	-0.303	0.308	-0.638	0.585	-0.086	0.279	0.094
	(0.118)	(0.263)	(0.245)	(0.436)	(0.343)	(0.310)	(0.265)	(0.124)
	[N=41,298]	[41,415]	[41,306]	[41,312]	[41,320]	[41,315]	[41,306]	[41,292]
Baseline mean	5.0	12.5	15.0	39.8	23.4	44.9	22.6	2.8
Concentrated	-0.052	0.902***	-0.037	0.831	0.376	0.134	0.511	0.194
	(0.205)	(0.367)	(0.348)	(0.532)	(0.449)	(0.419)	(0.311)	(0.162)
	[N=31,640]	[31,752]	[31,731]	[31,740]	[31,732]	[31,735]	[31,721]	[31,684]
Baseline mean	5.1	13.4	14.2	38.2	27.7	49.5	21.9	1.7

Notes: Each cell reports the coefficient from facility-level regressions of the corresponding outcome on exposure to nearby nursing home closures within the specified radius. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Baseline means are pre-closure sample averages.

Table A8: Effects of Nursing Home Closures on Occupancy and Staffing (Radius Sensitivity)

	Occupancy Rate	CNA HPRD	LPN HPRD	RN HPRD
Panel A. 15-mile radius				
Full Sample	0.069	-0.012	0.004	-0.004
	(0.220)	(0.012)	(0.008)	(0.004)
	[N=73,878]	[76,685]	[76,314]	[75,670]
Baseline mean	82.8	2.4	0.9	0.5
Competitive	0.069	-0.008	-0.008	0.006
	(0.234)	(0.016)	(0.010)	(0.005)
	[N=35,896]	[37,268]	[36,974]	[36,729]
Baseline mean	83.3	2.4	0.9	0.5
Concentrated	0.346	-0.037*	0.014	-0.016**
	(0.437)	(0.019)	(0.009)	(0.008)
	[N=31,290]	[32,347]	[32,389]	[32,053]
Baseline mean	81.4	2.3	0.8	0.4
Panel B. 10-mile radius				
Full Sample	0.051	0.004	0.012*	-0.004
	(0.222)	(0.009)	(0.006)	(0.004)
	[N=78,456]	[81,445]	[81,067]	[80,409]
Baseline mean	83.5	2.4	0.8	0.5
Competitive	-0.068	0.008	0.001	-0.002
	(0.210)	(0.010)	(0.006)	(0.004)
	[N=39,935]	[41,468]	[41,167]	[40,901]
Baseline mean	83.8	2.4	0.9	0.5
Concentrated	-0.068	-0.029	0.018	-0.006
	(0.577)	(0.025)	(0.011)	(0.011)
	[N=31,773]	[32,851]	[32,893]	[32,564]
Baseline mean	82.1	2.3	0.8	0.4
Panel C. 5-mile radius				
Full Sample	0.331	0.006	0.015**	-0.012**
	(0.247)	(0.012)	(0.007)	(0.005)
	[N=82,453]	[85,708]	[85,274]	[84,525]
Baseline mean	83.5	2.4	0.8	0.5
Competitive	0.232	0.012	0.012*	-0.011*
	(0.232)	(0.013)	(0.007)	(0.006)
	[N=43,645]	[45,437]	[45,073]	[44,723]
Baseline mean	83.9	2.4	0.8	0.5
Concentrated	0.221	-0.010	0.042	0.008
	(0.868)	(0.035)	(0.038)	(0.022)
	[N=32,032]	[33,110]	[33,159]	[32,830]
Baseline mean	81.5	2.2	0.8	0.4

Notes: Each cell reports the estimated effect of nearby nursing home closures on occupancy and staffing intensity at varying distance radii. Standard errors clustered at the county level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. HPRD is hours per resident day.