Disruption and Displacement in Health Care: Evidence from Nursing Home Closures

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Abstract

This paper examines the impacts of health care provider exits on patient outcomes and displacement. Leveraging data on the universe of long-stay nursing home patients, I estimate the mortality effects of 1,104 nursing home closures using a difference-in-differences approach. Displaced residents face a substantial short-run increase in mortality, with this disruption effect strongest among older and frailer patients. However, surviving patients tend to transfer to higher-quality providers. I find suggestive evidence that for certain subgroups this reallocation may lead to improved long-term survival, net of the initial disruption effect. The findings highlight the immediate health risks of displacement and the potential for quality-driven reallocation to mitigate them.

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1 Introduction

The U.S. nursing home industry has been in a state of decline for decades, as public reimbursement rates have stagnated and alternative forms of long-term care have proliferated. Nearly 15% of facilities have exited since 2000, representing a 10% reduction in aggregate capacity and raising concerns over access to care, particularly in rural markets. Despite these trends, little is known about the consequences of these closures for incumbent residents who are displaced, nor about how they reallocate to new providers.

Disruption and displacement caused by nursing home closures can have severe consequences for incumbent residents. The sudden loss of familiar caregivers, forced relocations to new and unfamiliar environments, and potential declines in care quality during the final weeks of a closing facility's operations can lead to acute health risks, particularly for older and medically fragile patients. Nevertheless, nursing home closures may entail countervailing forces for displaced residents. Facilities that exit due to financial fragility may be lower quality than replacement-level alternatives, and so displaced residents may find themselves reallocated to higher quality facilities, thereby improving health outcomes and extending their longevity. Both of these forces are important for understanding the consequences of the on-going contraction in the nursing home industry.

In this paper, I study the mortality effects of 1,104 nursing home closures for incumbent long-staying residents. To explore the trade-offs between the immediate disruptive costs and the potential long-term benefits of forced displacement, I estimate both short-run and long-run mortality effects using a matched difference-in-differences design applied to administrative data on the universe of long-stay nursing home residents. I find that nursing home residents experience a 1.18 percentage point increase in their short-run risk of mortality after the facility closes, representing a 16.3% increase over the baseline rate. This short-run mortality spike is present for all groups, but is largest for patients who are relatively older and sicker. After this initial spike, differential mortality risk among surviving patients decreases over time, eventually turning negative. Inclusive of the initial increase, I find suggestive evidence that cumulative mortality three years after closure is 1.16 percentage points lower than if the facility had not exited, although both the point estimates and statistical significance of this decline varies across samples. Older and sicker residents experience only the sharp short-run increases in mortality; point estimates for these groups indicate no survival gains. These results are not driven by short-term mortality displacement, also known as "harvesting." Using both state-issued deficiency citations and a risk-adjusted survival measure, I find that exiting facilities are of particularly low quality, and that surviving patients reallocate to higher-quality firms. Patients that experience the largest expected quality improvements appear to experience long-run survival gains.

I also find considerable treatment effect heterogeneity by local facility capacity, consistent with widespread media concerns over diminishing rural nursing home access (Healy 2019; Saslow 2019). The pattern of cumulative mortality decline appears to accrue only to residents in competitive nursing home markets. In contrast, patients in areas with few remaining facilities experience the sharpest increases in mortality risk but no sign of long-term survival gains. Moreover, I find that for-profit firm exits generate the largest survival gains, whereas non-profit exits generate no survival improvements.[1] These findings speak to the common tradeoff between access and quality in health care. These forced relocations may displace residents to higher quality facilities, but do so at the cost of distance from family and immediate disruption. For clinically fragile patients, or those in areas with few remaining options, this cost may dominate any quality gain. This implies that for these patients, maintaining continuity of care is crucial, even as prospective patients who are shielded from the disruptive effects may benefit from the reallocation.

This study's focus is the health impact of disruptive facility closures on incumbent, 'long-stay' nursing home residents, roughly defined as those patients whose stays exceed 90 days. It is important to note that there are other patients who may be impacted by a facility closure. For example, my research design does not assess the impacts for 'short-stay' nursing home residents, who primarily receive rehabilitative post-acute care in anticipation of being discharged back to the community within days or weeks. These patients typically have different health profiles and care needs relative to long-stay residents, who may reside in a facility for months or years and primarily require custodial care, such as assistance with the activities of daily living (e.g., bathing, dressing, and eating). Accordingly, my results may not generalize to the short-stay patient population, for whom displacement effects are unlikely to be first-order concerns owing to their brief lengths of stay. Moreover, depending on complementarities in production between short- and long-stay care, the impacts of *which* facilities close may differ between short- and long-stay residents. Recent work by Templeton et al. (2023) demonstrates that short-stay patients benefit more from receiving care at facilities that specialize in treating such patients. If facilities specializing in long-term care are more likely to exit, then short-stay patients may benefit relatively more from being redirected to primarily post-acute facilities. Although it is not the focus of this paper, the improvements from removing low-quality providers that I document are likely to benefit short-stay patients as well.

The long-stay nursing home population is worthy of independent study for several reasons. Long-stayers are quantitatively important for both providers and insurers; while the majority of *patients* are short-stayers (long-stayers represent approximately 27% of patients over the period 2000-2017), long-stayers contribute the vast majority of *days* (approximately 67%). Accordingly, long-stay patients hold particular policy-relevance from a public finance perspective, as much of this care is funded on a per diem basis by state Medicaid programs. Indeed, long-term nursing home care comprises the majority of fee-for-service spending in such programs (Centers for Medicare & Medicaid Services 2022). Even outside of the nursing home, these patients command disproportionate shares of aggregate medical spending. Annual Medicare spending for patients beginning a long-stay nursing home episode in the following year is approximately $15,641 per patient, compared to only $13,280 for short-stay patients (Appendix Table D.1). Consequently, changes in the availability and quality of long-term care facilities can have substantial fiscal implications for both federal and state governments. Finally, despite their economic significance, research on the

1. This result is consistent with the robust finding that non-profit nursing homes tend to provider higher quality care (e.g., Grabowski and Stevenson 2008), though it may also reflect for-profits' ability to mitigate the short-run disruptions associated with closure.

health and well-being of long-stay nursing home residents remains relatively limited compared to the short-stay population. Recent literature on the economics of nursing homes has largely focused on short-stay patients, emphasizing short-term outcomes relevant to this group (e.g., Gupta et al. 2023; Einav, Finkelstein, and Mahoney 2022; Olenski and Sacher 2022). This paper addresses this gap by contributing to the relatively scant body of work studying the long-stay population.

This paper contributes to several distinct literatures. Primarily, I contribute to a growing literature on the implications of health care provider exits for patients. This work has largely focused on exits of hospitals (Carroll 2019; Battaglia 2022; Joynt et al. 2015) and primary care physicians (Sabety 2023; Kwok 2019; Schwab 2021), and has generally found adverse consequences for health outcomes, though several studies report some efficiency gains. Perhaps most closely related to my study is the recent work by Fischer, Royer, and White (2024) studying hospital obstetric unit closures, which similarly finds large geographic displacement paired with improvements in quality. My findings extend this literature to nursing home exits. There are several reasons to believe that nursing home closures may have more accentuated effects on patients than other provider exits. Long-term care patients are by definition in poor health, even preceding a closure. Closures necessitate particularly costly moves for residents, as long-term care facilities are communities themselves, and residents develop personal connections with the staff and their fellow patients which may otherwise persist for years.

In this spirit, my paper builds upon an older clinical literature examining the impact of forced relocations on nursing home resident health and well-being. This literature details individual case studies of particular facility relocations, though the impacts on mortality are mixed and sample sizes tend to be small (typically restricted to residents of only one or two facilities). Consistent with my results, Laughlin et al. (2007), Castle and Engberg (2011), and Falk, Wijk, and Persson (2011) examine forcibly displaced residents in the U.S. and Sweden, finding modest increases in mortality for patients who are relocated from a nursing home. In contrast, several studies have reported either no changes in mortality (Mirotznik and Kamp 2000; Meehan et al. 2004), or improvements for displaced residents (Thorson and Davis 2000). Holder and Jolley (2012) reviews this literature and concludes that while the effects of forced relocations are mixed, more organized relocations can moderate the negative consequences. My paper is broadly consistent with these studies, while building upon their groundwork. Chiefly, much of the prior literature is limited in scope and generalizability due to their small sample sizes, often exclude control groups in their analyses, and typically focus on the immediate aftermath of a displacement. Crucially, no prior study examining longer run effects has accounted for changes in mortality rates due to selective sample attrition ("harvesting"), as I discuss in this paper. This study is the first to use a large-scale administrative dataset to estimate the systematic effects of nursing home closures on patient outcomes in both the short- and long-run.

I also contribute to the small but growing body of research on the economics of the nursing home industry (Grabowski, Gruber, and Angelelli 2008; Lin 2015; Ching, Hayashi, and Wang 2015; Hackmann 2019; Gandhi 2020; Gandhi, Song, and Upadrashta 2020; Gupta et al. 2023; Hackmann, Pohl, and Ziebarth 2024; Gandhi et al. 2024; Antill et al. 2025). The implications of my results for nursing home quality, pertaining to long-stay residents, also complement two recent working papers by Olenski and Sacher (2022) and Einav, Finkelstein, and Mahoney (2022) which estimate facility-level quality for short-stay nursing home patients.

A final contribution is to the well-developed literature in industrial organization on consumer reallocation and firm productivity (Olley and Pakes 1996; Foster, Haltiwanger, and Krizan 2006; Foster, Haltiwanger, and Syverson 2008). Syverson (2011) and De Loecker and Syverson (2021) provide overviews of this literature spanning multiple sectors. A robust empirical finding of this literature is that lower productivity firms are more likely to exit. Chandra et al. (2016) note that in health care markets, because consumers bear a low share of the costs of production, it is more sensible to view competition over quality rather than conventional productivity measures. Adopting this framework, my reallocation results support extending this result to the health care sector.

The remainder of the paper proceeds as follows. Section 2 provides a brief industry background, highlights critical institutional details, and reviews the data used in each step of the analysis. Section 3 presents the research design, while Section 4 contains the results. Section 5 concludes.

2 Setting and Data

Skilled nursing facilities, commonly referred to as nursing homes, are certified to provide care and receive public reimbursement by the Centers for Medicare & Medicaid Services (CMS). Nursing homes provide a broad array of services, including both short-term post-acute rehabilitative therapy as well as routine nursing services for long-stay residents who are incapable of living independently. Long-term care patients suffering from chronic conditions, such as Alzheimer's disease or a related dementia, have stays that may last years according to their longevity. As a consequence, nursing homes themselves constitute communities, and residents may form close bonds with staff and other patients. The closure of a nursing home – resulting in a scattering of residents and staff – is a displacement of individuals from their community and may therefore have deleterious impacts on resident health and well-being.

2.1 Recent Trends in U.S. Nursing Home Entry and Exit

The nursing home industry is a substantial component of the economy. Comprising just under 1% of U.S. gross domestic product and housing 2.3% of the senior population, nursing homes lag behind only hospitals, physicians, and pharmaceuticals in national personal care expenditures. This scale points to a substantial public interest in the industry, as the majority of nursing home care is publicly financed, representing about 6% of all government health care spending.[2]

Despite the market's size and aging demographics, the nursing home industry has been marked by an aggregate decline over the past few decades. From 2000 to 2017, the total number of facilities

2. Estimates of nursing home consumption costs are from the National Health Expenditure accounts. The National Center for Health Statistics estimates there were approximately 1.3 million nursing home residents in the U.S. in 2020, compared to approximately 55 million adults aged 65 and over.

shrank 11.8% from 16,964 to 14,956 (Figure 1, panel (a)), even as the senior population grew by more than 50%. This contraction is marked by considerable geographic heterogeneity. As is true for many basic medical services, rural areas have been particularly hard hit by diminishing access to nursing home care. Rural counties have experienced the steepest declines in capacity over this period. Nationally, the median number of beds per 100 seniors in a county fell from 5.7 to 3.5, with the largest declines occurring in Midwestern states (Figure 1, panel (b)). This wave of rural nursing home exits has generated considerable media attention, documenting stories of residents who are displaced by 50+ miles and emphasizing the burden such closures place on their families (Healy 2019; Saslow 2019).

Both firms and industry analysts widely believe that the primary culprit behind the wave of nursing home closures is insufficient public (Medicaid) reimbursement rates. Annual trade association reports find that rates routinely fall below the cost of providing care, such that each additional Medicaid patient results in average losses for facilities ranging from $5 to $70 per day (AHCA 2018), with several ongoing lawsuits brought by providers against states alleging that rates have failed to keep up with costs over time. Nursing homes with lower Medicaid rates and higher shares of Medicaid residents report lower profit and are routinely found to be more likely to exit (Castle et al. 2009; Zinn et al. 2009). I replicate these results using an annual panel of nursing homes from 2011 to 2019 (Appendix Figure D.1). As expected, firms with higher occupancy rates and lower shares of Medicaid patients report higher variable profit, and the probability of exit is decreasing in variable profit.[3]

The declining profitability of the industry likely also explains the lack of offsetting entry over this period. As the nursing home industry has contracted, there has been a corresponding boom in alternative forms of senior living arrangements, such as assisted living, which are not certified by CMS to provide the same level of care. These facilities are much less heavily regulated than nursing homes, and accept only private-pay residents, with few exceptions. Although these facilities may be alternatives for patients with lighter care needs, those patients who do require routine nursing services are left with fewer options.

The closure process itself is governed by state-level policies during my sample window. While these can vary by state, there are common themes. Typically, facility administrators are required to provide written notice of closure to residents and their families as well as a state long-term care ombudsman at least 60 days prior to the closure. This notice includes a closure plan detailing the process for the safe transfer of residents to alternative facilities that align with their needs and preferences (California State Legislature 2020). The closure plan serves as a roadmap to ensure minimal disruption to residents' care and quality of life, and includes a relocation evaluation for each resident. In practice, the relocation process involves significant coordination between the closing facility's staff and the residents/their families, as well as receiving facilities. Challenges arise when there are few nearby facilities to receive patients. In such cases, patients may be transferred to

3. Gandhi and Olenski (2024) find that estimates of fixed costs (primarily rents and management fees) are artificially inflated through self-dealing. Accordingly, I report results using only variable profit.

distant facilities, placing a burden on residents and their families.

2.2 Quality of Care: Public Concerns and Measurement Issues

The low quality of nursing home care has been a source of tremendous concern for both researchers and policymakers for decades (Institute of Medicine 1986). Residents routinely suffer harm directly due to their care. A recent *New York Times* exposé details the horrific conditions that many nursing home residents face, including neglect, abuse, and even death (Silver-Greenberg and Gebeloff 2021). Such instances – including the assault of patients, presence of maggots in prepared foods, and bed sores deep enough to reveal bone – are not cherry-picked examples. One in three Medicare nursing home patients experienced an adverse event leading to harm or death as a result of their care (Office of Inspector General 2014).

These violations are documented by state health inspectors. To be eligible for public reimbursement, facilities must undergo regular inspection surveys as part of a broader re-certification process, as well as in response to complaints. State inspectors follow staff as they work, interview residents, and comb through medical records to identify problems and issue deficiency citations when they encounter problems. In this paper, I focus on "quality-of-care" violations (such as nursing or pharmacy infractions), as these most plausibly contribute to resident mortality. Such deficiencies are quite common. In 2013, approximately 93% of firms received at least one deficiency, and one in five facilities received severe deficiencies for causing (at least the potential for) actual harm or jeopardy to residents (Harrington et al. 2016; Harrington et al. 2018).

Of course, deficiency citations are not the only possible measure of nursing home quality. However, many existing quality measures are either better tailored for the short-stay nursing home population (for example, hospital readmissions or mortality), or derived from data that nursing homes themselves submit and is subject to potential misreporting (Thomas 2014; Silver-Greenberg and Gebeloff 2021). For these reasons, I rely on the broadly available quality-of-care deficiencies, which are relevant for all patient populations, and generated outside the nursing home's control. Nonetheless, to examine the robustness of this measure, I also examine reallocation using a risk-adjusted 90-day survival measure, the construction of which is described in Appendix C.

2.3 Data Sources

I combine several sources of administrative data from CMS along with publicly available data on nursing home characteristics. The core of my analysis comes from resident-level assessment data from the Minimum Data Set (MDS), which covers the universe of nursing home patients spanning 2000-2017. All CMS-certified nursing homes are required to complete (at least) quarterly assessments of each resident, beginning at admission and ending at discharge. The MDS, increasingly popular among researchers, collects a wide range of clinical information used by staff to guide care plans, and by payers to determine reimbursement rates. I use these data to construct a quarterly panel of nursing home residents.

The MDS panel is supplemented with the universe of Medicare enrollment and fee-for-service claims data. By linking the MDS to Medicare data, I am able to track patients after nursing home discharge, allowing me to observe mortality, home zip codes prior to admission, movement across facilities, and health care utilization over time. My study population is therefore the universe of nursing home residents who are enrolled in the Medicare program, regardless of their payer source for nursing home care. I measure short-stay acute care hospitalizations for the 88.0% of my sample who are enrolled in Fee-for-Service (Traditional) Medicare using the Medicare Provider and Analysis Review (MedPAR) files.

In addition to these administrative data, I also combine a variety of publicly available datasets on nursing home characteristics. I measure quality using the annual number of deficiency citations, collected from Nursing Home Compare. I identify dates of termination from Medicare and Medicaid billing using the CMS Provider of Service files, which I use in conjunction with other sources to identify facility exits (algorithm described in Appendix Section A.2). To collect facility variables, such as addresses, bed counts, and annual snapshots of occupancy and payer composition, I use the OSCAR/CASPER data, accessed through LTCFocus.org.[4] All data sources used, their years spanned, and their application in this project are summarized in Appendix Table D.2.

2.4 Exit and Mortality

Figure 2 presents preliminary empirical evidence on the relationship between nursing home exit and initial resident mortality, as well as subsequent long-term survival. Panel (a) demonstrates the first empirical finding of this paper. Using the MDS assessments and the dates of death from the Medicare enrollment records, I plot the facility-level raw quarterly mortality rate of all long-stay residents present in an exiting firm. The quarterly mortality rate remains flat in the period preceding the shutdown date, and then spikes in the quarter of exit. This sharp increase suggests a substantial sudden mortality cost associated with nursing home exits. Identifying the effect of an nursing home exit – rather than simply changes in the sample composition – will require fixing a baseline sample, as well as constructing a control group, which I detail in Section 3.

To explore the long-run effects of exit on resident survival, I plot the unadjusted cumulative survival (Kaplan-Meier curves) of all displaced residents who were present in a closing facility two quarters prior to exit in Figure 2 panel (b). I also plot the corresponding survival curves for a matched control sample, consisting of residents in observably similar facilities that did not exit, explained in more depth in Section 3. These curves illustrate the second empirical finding: the long-run survival rate for the displaced residents lies *above* the survival rate for residents who were not affected by a closure, suggesting that the closures may induce survival-improving reallocation.

Taken together, these figures highlight the two major empirical findings of this paper. First, nursing home closures are associated with a substantial increase in quarterly resident mortality. Second, long-run survival for displaced patients trends above the corresponding survival for residents

4. LTCFocus is sponsored by the National Institute on Aging (1P01AG027296) through a cooperative agreement with the Brown University School of Public Health.

unaffected by a closure. Estimating the relative magnitudes of these two effects, and exploring the mechanisms behind any quality-improving reallocation, require a formal empirical strategy to identify the causal effect of nursing home exit.

3 Empirical Approach

3.1 Research Design and Estimation Sample

Estimating the causal effect of nursing home exits on mortality requires constructing counterfactual resident survival rates in the absence of a closure. I do so by examining how mortality evolves among nursing home patients residing in comparable facilities that did not close. Because closures do not occur at random, the universe of non-exiting firms may offer an inadequate control group if the residents of exiting firms systematically differ in their mortality trends.

To address this concern, I construct a matched sample of non-exiting nursing homes which are observably similar to the set of closing facilities in the year prior to exit.[5] I match each exiting facility with up to four control facilities on the similarity of their characteristics (measured with Mahalanobis distance): occupancy, the shares of private-pay and Medicaid patients, for-profit status, bed counts, chain ownership, market concentration, levels of staffing, and county population. Compared to the universe of non-exiting firms, exiting firms are smaller, less likely to have a specialty care unit, and have significantly more Medicaid patients than the universe of non-exiting firms. Matched firms are closer in size (84.6 beds compared to 94.6), have comparable shares of private-pay patients (approximately 19%), and are similarly distributed across rural and urban areas (Appendix Table D.3). Further details on the matching procedure are provided in Appendix A.

This matching approach to estimating the causal effect of a nursing home closure hinges on the identification assumption that resident mortality risk in the treatment group would have evolved in parallel with the control group absent the closure. Specifically, I assume that the firms' shut-down decisions – which may be endogenous to demand (recall from Section 2.1 that the number and type of patients are key determinants of profits, which predict exit) – are orthogonal to any idiosyncratic health shocks to *incumbent* residents in the period around the closure. That is, the crucial assumption is that mortality rates between residents of the treatment and control facilities would have trended in parallel in the absence of exit.

Identifying the mortality effects of a nursing home closure also requires defining the set of long-stay patients who are impacted by the exit.[6] The residents who remain in a facility until the shutdown date may be a selected sample, as they may be the least attentive to the firm's financial fragility. Moreover, families may hesitate to transfer a patient who is too frail to travel, raising questions about generalizability and the plausibility of the parallel trends assumption. Such an

5. This approach mirrors recent studies of the effects of provider exits on patient outcomes (e.g. Sabety 2023).

6. Recall that my focus is on long-staying residents, rather than rehabilitation-focused short-stay patients. Short-stay residents are less likely to be directly impacted by a closure, as their lengths of stay are (by definition) shorter than the 60-day notification window.

approach would also miss the early effects of a closure: as the staff depart for new employment, facility quality may deteriorate just prior to the shutdown date, and so restricting to only the last remaining patients may ignore the initial impacts of an exit. Conversely, choosing a sample of baseline residents who were present long before the closure date may generate attenuation bias due to patient attrition, as residents may die or transfer out of the facility prior to treatment, for reasons unrelated to the closure. The right threshold for choosing the sample of affected residents is one that balances these tradeoffs.

Examining the daily counts of assessments in the year prior to exit, I find that facilities begin to discharge patients approximately 90 days before their termination date from the Medicare and Medicaid programs, at which point new admissions also begin to taper (Appendix Figure D.3). These patterns motivate a baseline cohort of treated residents as those who are in the facility two quarters prior to the exit date.[7] This window is near enough to the termination date to allow for the possibility that some patients will be discharged prior to exit, but not so far that the treatment effect of exiting will be attenuated. To assess the parallel trends assumption implicit in the difference-in-differences approach, I follow Deryugina and Molitor (2020) and construct a second cohort of residents who were present four quarters prior to exit. While the treatment effect of the exit will be attenuated for this cohort because they may be discharged or die prior to the exit date, I will use this cohort to examine the extent to which the mortality rates of the treatment and control groups move in parallel prior to closure. To construct the control groups, I apply the same criteria to the matched control facilities, selecting residents who are present two and four quarters prior to the matched treated facility's exit date, respectively.

This procedure results in 42,942 treated patients and 208,553 control patients during the window 2001-2014.[8] Table 1 contains summary statistics on the resident samples. Patient characteristics are similar between the exiting and matched facilities. There is slight remaining imbalance between the two – residents of closing facilities are less likely to be white (78.5% vs 80.6%) or female (65.8% vs 69.8%), and are slightly younger (78.7 vs 80.7 years at time of closure). These patients are very long-stayers: the typical patient is present for nearly two years prior to closure, with similar lengths of stay between the treatment and control groups (Appendix Figure D.4). Although difference-in-differences does not require balance in levels, I nonetheless address this remaining imbalance by including a rich set of demographic and chronic condition controls in the event study estimation. To assess the sensitivity of the results to these controls, I also examine the stability of the coefficients by iteratively adding different sets of controls, and find that the point estimates are quite stable (Section 4).

7. I rely on quarterly and annual assessments, rather than new admission assessments, to identify long-stay patients rather than the post-acute short-stay patients likely to be discharged prior to exit (Huang and Bowblis 2019).

8. I restrict the sample of exits to ensure one year of pre-treatment and three years of post-treatment observations.

3.2 Quarterly and Cumulative Mortality

The baseline resident panel begins two quarters prior to the nursing home exit, $\tau = -2$, and runs through 2017 or the individual's death. That is, patients exit the sample after their death has been recorded, as they are no longer at risk of dying. Crucially, because I measure mortality through the Medicare enrollment records, rather than as recorded by the nursing home, I am able to track patient mortality following discharge.

To establish the effect of a nursing home exit on quarterly mortality risk, I estimate the following regression:

$$Y_{it} = \sum_{\tau=-1}^{12} \beta^\tau d_{it}^\tau \times \text{Exit}_{j(i)} + \mu_{j(i)} + \lambda_{c(i)t} + \delta X_i + \varepsilon_{it} \tag{1}$$

where Y_{it} is an outcome for individual i in quarter t, such as mortality. Relative time indicators d_{it}^τ denote the quarters around the facility exit. X_i is a vector of patient-level covariates, including demographics and chronic conditions present at baseline. I also include two sets of fixed effects: $\mu_{j(i)}$ is a fixed effect for the resident's initial nursing home at baseline, $\tau = -2$, and $\lambda_{c(i)t}$ is a matched cohort-by-quarter fixed effect, where cohorts are defined as the exiting facility and its matched controls. The facility fixed effects, $\mu_{j(i)}$, permit level differences in mortality rates across facilities. The cohort-quarter fixed effects, $\lambda_{c(i)t}$, account for common time series variation within each cohort in a flexible, non-parametric way. Cohort-quarter fixed effects subsume standard quarter fixed effects, and permit time trends to differ between match cohorts. For instance, if rural facilities tend to have more rapid mortality growth than urban facilities, cohort-quarter fixed effects will capture these differential trends (recall that county density is one of the matching variables). Combined, these fixed effects isolate the variation in mortality rates between an exiting facility and its matched controls at each time period. This practice follows the literature using matched differences-in-differences (e.g. Gandhi, Song, and Upadrashta 2020). Standard errors are clustered at the original facility-level.[9]

The focal parameters, β_τ, capture the causal effect of a facility closure on residents' quarterly mortality hazard. Each β_τ measures how the change in mortality risk between quarter τ and the reference period differs for residents of closing facilities relative to residents in matched non-closing facilities. Accordingly, the identifying assumption is that, absent a closure, changes in the quarterly hazard of death would have evolved in parallel between the treatment and control groups. This permits baseline differences in mortality levels across facilities or residents—such differences are absorbed by the facility fixed effects $\mu_{j(i)}$—while requiring only that the evolution of hazards be comparable in the absence of exit. The sequence of β_τ therefore traces how the mortality risk trajectory of the displaced resident diverges from what it would have been had the closure not

9. Clustering is done at the original facility level, rather than the level of the current facility, for several reasons. The original facility is the level at which treatment is assigned (Abadie et al. 2023), making it the natural unit at which to cluster. Moreover, because patients move across facilities, clustering at the current facility-level would fail to account for any within-patient intertemporal correlation.

occurred.

The quarterly mortality effects β^τ estimate the change in the hazard rate induced by the exit, but reveal nothing about the cumulative effect on survival. Changes in β^τ may reflect compositional changes, as relatively frailer residents may die from the shock, resulting in a healthier remaining pool of patients in the treatment group. To accommodate this concern, I follow Deryugina and Molitor (2020) and compute the cumulative mortality effect for each relative quarter t:

$$\Delta M_t = \prod_{\tau=-1}^{t} (1 - m_\tau + \beta^\tau) - \prod_{\tau=-1}^{t} (1 - m_\tau) \tag{2}$$

where m_τ is the empirical fraction of the treated residents who die in quarter τ. ΔM_t is the (negative) difference between the treatment group's observed survival rate to period t and the counterfactual survival rate the group would have experienced had treatment not occurred.[10] I estimate ΔM_t and its analytic standard error using the β^τ estimates from equation (1) and the delta method.

Note that although the cumulative mortality effect is the primary object of interest, it is not feasible to estimate ΔM_t directly, e.g. by comparing the survival curves between treated and control cohorts. This is because survival rates must converge to zero for all cohorts. Accordingly, any level difference in baseline mortality mechanically requires that the survival curves not move in parallel. There is no such restriction on the quarterly mortality hazards, and so I use β^τ to calculate the implied changes in cumulative mortality.

Deaner and Ku (2024) formalize this insight, showing that when outcomes represent entry into an absorbing state (such as death), the standard parallel trends assumption on mean outcomes fails mechanically and should instead be applied to hazard rates. My implementation follows Deryugina and Molitor (2020), which applies the same identification logic: I estimate the hazards directly at the individual-quarter level, allowing for facility and cohort fixed effects and rich covariate adjustment. Appendix B illustrates the same principle with a simulation showing how direct estimation using survival levels leads to spurious pre-trends and biased estimates when baseline mortality differs across groups.

3.3 Mechanisms

The flexibility of the difference-in-differences regression in equation (1) allows me to consider alternative dependent variables, which may provide evidence on the mechanisms behind any mortality results.

Reallocation Across Providers – One advantage of the administrative data is the ability to track the same resident across providers, allowing me to examine how displaced patients reallocate following a facility exit. To examine changes in quality, I re-estimate equation (1), replacing the

10. Deryugina and Molitor (2020) provide the derivation of equation (2). Notice $\Delta M_t = (1 - S_t^O) - (1 - S_t^C) = S_t^C - S_t^O$, where $S_t^O = \prod_{\tau=-1}^{t}(1 - m_\tau)$ and $S_t^C = \prod_{\tau=-1}^{t}(1 - m_\tau + \beta^\tau)$ are the observed and counterfactual survival rates, respectively.

dependent variable with various measures of the nursing home I observe resident i in at quarter t. In particular, I study the change in the number of quality-of-care deficiencies, as well as a measure of facility-level risk-adjusted survival, estimated prior to exit. Leaning on the enrollment data, I compute the distance between the resident's last observed zip code prior to nursing home admission and their nursing home as of quarter t, allowing me to examine how far residents are displaced.

Hospitalization – In addition to the nursing home assessment data, I also observe the universe of short-stay acute care admissions for the 88.0% of my sample who are enrolled in fee-for-service Traditional Medicare, rather than a Medicare Advantage plan. Restricting my analysis to this subsample, I can examine how hospitalizations evolve following a nursing home exit, which is informative of the drivers behind any mortality results. Because the MDS does not contain any cause of death codes, I am restricted to approximating cause of death using the primary diagnosis code of any inpatient hospitalizations ending with death. I classify the primary diagnoses into Major Diagnostic Categories (MDC), a common inpatient categorization. I then re-estimate equation (1), replacing the dependent variable with an indicator for whether the resident died in-hospital with each MDC code.

Additionally, I examine how nursing homes themselves contribute to the mortality effect. Walsh et al. (2012) identify a set of primary diagnoses (such as infections, falls, and bed sores) that, when long-stay residents are hospitalized with them, indicate poor nursing home quality. Increases in 'preventable' hospitalization with these diagnoses during the period of a nursing home exit may reflect the facility's failure to provide adequate care during the transition. As before, I re-estimate equation (1), replacing the dependent variable with an indicator for whether the resident was hospitalized with any of these diagnoses. With all hospitalization regressions, I summarize the dynamic treatment effects d_{it}^{τ} in equation (1) into short-run (relative quarters zero and one) and long-run (relative quarters two and up) effects for brevity.

4 Results

4.1 Effects of Nursing Home Exits on Mortality

Overall Mortality — The quarterly (β^{τ}) and cumulative (ΔM_t) mortality estimates are plotted in Figure 3 and summarized in Table 2. Panel (a) presents the main results, for the resident cohort present in relative quarter $\tau = -2$. These results indicate a sharp short-run[11] increase of 1.18 percentage points in quarterly mortality for long-term care residents of nursing homes that exit. This is a frail group of patients — the baseline quarterly mortality in the control group is 7.2% — and so the estimates correspond to an approximately 16.3% relative increase in mortality risk during the quarter of nursing home exit. Following the initial increase in mortality risk, changes in cumulative mortality fall and become negative by the eighth quarter after closure. Cumulative mortality continues to decline, and by the third year after closure settles at 1.16 percentage points *lower* than if resident mortality rates had evolved parallel to the control group. Extending the

11. Here, and throughout the paper, short-run refers to the quarter of the closure as well as the subsequent quarter.

sample to include 16 post-treatment quarters suggests that the cumulative mortality estimates stabilize after the 12th quarter (Appendix Figure D.5).

To assess the validity of this assumption – that the treatment and control group mortality rates would have evolved in parallel in the absence of a nursing home exit – I construct a separate cohort to examine any differences in pre-trends. Figure 3 panel (b) presents estimates for a cohort of residents who were present in the nursing home one year prior to exit. There is no diverging mortality trend between the treatment and control groups in the time leading up to the event. Moreover, I find very similar point estimates using this sample as I do with the $\tau = -2$ cohort, although the long-run mortality decline is not statistically significant. Of course, the further back the baseline period is set the more the treatment effect becomes attenuated due to attrition, and so I use the $\tau = -2$ cohort for estimation of the main effects.

Patient Heterogeneity — Given the heterogeneity in health across nursing home patient types, I consider whether this pattern of initial shock and subsequent improvement varies across clinically meaningful patient covariates. A large share (57.0%) of long-term residents suffer from Alzheimer's disease or a related dementia. These are patients for whom transfers to another facility (a sudden change in environment) may be particularly costly. I examine heterogeneity in the mortality effect by Alzheimer's status in Figure 3 panels (c)-(d). Indeed, I find a particularly large initial mortality effect of 1.71 percentage points in this subgroup. Similar heterogeneity exists when subsetting by age at baseline (panels (e)-(f)): patients who are at least 80 years old experience an extremely sharp 2.03 percentage point increase in mortality immediately after closure, whereas younger patients experience only a 0.45 percentage point increase.

Robustness — To assess the importance of risk-adjustment (the patient-level covariates X_{it} in equation (1)), I estimate several cumulative mortality effects, iteratively adding more patient covariates. The stability of these results across specifications demonstrates that the role of the covariates is limited (Appendix Figure D.6, which omits the estimates of β^{τ} for visual clarity). The inclusion of demographic controls very slightly attenuates the estimates of ΔM_t, and the additional health status indicators (fixed at baseline) from the MDS also very slightly attenuate the estimates. I also consider an alternative specification, in which I include 24 chronic condition indicators which are derived from Medicare claims, available from the Beneficiary Summary File. These controls have the benefit of accounting for an exhaustive list of chronic conditions, but unfortunately are defined only for the approximately 88.0% of patients who are enrolled in Traditional Medicare, and so the results that rely only on the MDS are my preferred specification. I find very similar effects using this specification (Appendix Figure D.7). These results suggest that concern over the residual imbalance indicated by Table 1 is minimal. Note that 6.9% of facility closures in my data are so-called 'involuntary' terminations from Medicare/Medicaid, which may result from particularly severe quality violations. To examine the sensitivity of my results, I re-estimate the main mortality model excluding these facilities. Reassuringly, the estimates are nearly identical to those from the main results (Appendix Figure D.8). Finally, while the matching procedure does not include a direct measure of facility quality (due to limited data availability), I examine the sensitivity of my results to an alternative matching procedure that includes quality-of-care deficiency citations. The resulting estimates mirror those of my main results, though the reduction in sample size results in increased standard errors (Appendix Figure D.9).

4.2 Heterogeneity by Market Concentration

In light of the concerns over rural nursing home access detailed in Section 2.1, and the known geographic differences in nursing home contraction (Figure 1 bottom panel), I turn next to heterogeneity in the mortality effect of a closure by the level of local nursing home market concentration. Mirroring Gandhi, Song, and Upadrashta (2020)'s study of private equity acquisitions of nursing homes, I calculate a Herfindahl-Hirschman Index (HHI) using total bed capacity within 10 kilometers[12] of each facility in the year prior to exit. The distribution of resulting HHIs in the analysis sample is presented in Figure 4. Approximately 25% of facilities are at least duopolists (HHI $\geq 5,000$); these facilities are defined as operating in non-competitive markets, and the remainder as competitive.

I estimate equation (1) separately by each competition group. Figure 5 presents the results. I find strong evidence of treatment effect heterogeneity: residents of nursing homes in competitive markets experience the smallest initial spikes in quarterly mortality (1.14 percentage points), and by 12 quarters after closure have a cumulative mortality probability that is 1.68 percentage points lower. Conversely, residents of facilities in non-competitive areas experience a very large initial mortality increase in the period immediately following closure (1.30 percentage points), and at no point have a cumulative mortality effect that falls below zero. I also assess the validity of the parallel trends assumption in each of these subgroups, by examining effects in the 4-quarter cohort as well.

I examine to what extent these diverging effects are driven by compositional differences in ownership across different markets, given that for-profit facilities are commonly associated with lower quality. I re-examine the concentration results by restricting the sample to exiting for-profits and non-profits, separately. The cumulative mortality effects ΔM_t corresponding to separate regressions from each intersection of ownership status by market concentration are plotted in Figure 6.[13] The only patients who experience long-term survival improvements are those in for-profit facilities in competitive markets. Patients in non-profits that exit only experience large initial mortality spikes, and never enjoy survival gains, regardless of their market concentration. These results are consistent with the prior literature, which has found that non-profit nursing homes tend to provide higher quality care (Grabowski and Stevenson 2008). However, for-profit closures in competitive markets experience minimal short-run mortality costs, suggesting that it may be for-profits' ability to smoothly exit the market that drives some of the observed benefits. Fully

12. Although this radius is fairly tight, it is selected to match Gandhi, Song, and Upadrashta (2020) who note that given extremely patient strong preferences for nearby facilities, nursing home markets are much more localized than even a county, and so this radius exceeds the median distance traveled by patients (Hackmann 2019). Moreover, employing a county-level HHI measure generates nearly identical results (Appendix Figure D.10).

13. For clarity, I omit the quarterly mortality estimates β^{τ}.

disentangling the role of facility quality in mediating these survival effects requires more direct evidence on firm quality, which I turn to next by examining the role of patient reallocation.

4.3 Reallocation Across Facilities

Where do displaced residents go? In Figure 7 panel (a), I calculate the share of the surviving cohorts who remain in any nursing home by quarter (Appendix Figure D.11 for the 4-quarter cohort). For the treatment group in the post-exit period, this assessment necessarily occurs in a different facility. I find that the vast majority of residents do transfer to another facility, and that in the first quarter after closure, 85.0% of surviving residents still appear in another nursing home. The majority of patients transfer out of the closing nursing home during the quarter of closure, although exit in the quarter immediately prior is not uncommon (Appendix Figure D.12). To examine how much transferred patients contribute to the mortality increase, I re-estimate the mortality regression (1), while restricting my sample to continuous quarters in which the patient is still present in (any) nursing home. Because continuous residence in a nursing home is endogenous to mortality risk (i.e., the patient must survive long enough to reside in the new home), this exercise should be interpreted with caution. The mortality trends look similar in this subgroup of transferred patients (Appendix Figure D.13), although the effects are somewhat attenuated relative to the main sample.

An important welfare consideration in assessing nursing home closures is the distance patients must travel to seek care, which is known to reduce visitation from friends and family and thus increase feelings of isolation (Greene and Monahan 1982; Port et al. 2001; Gaugler 2005). Recent evidence during the Covid-19 pandemic of the deleterious effects of isolation on well-being further underscores the importance of family visitation for nursing home residents (Levere, Rowan, and Wysocki 2021; Stall et al. 2021). Revealed preferences indicate that geographic proximity is a dominant factor in long-term care choice, as residents overwhelmingly select nearby nursing homes over higher quality facilities.[14] The toll of long travel distances are well-described in several recent media accounts of the costs of the current wave of rural nursing home closures (Healy 2019; Saslow 2019). To examine how distance from home changes, I re-estimate equation (1), replacing the dependent variable with a distance measure from the patient's home zip code.[15] Both log (Figure 7 panel (b)) and linear (Appendix Figure D.14) specifications suggest a substantial increase in travel distances following nursing home closure, with the largest increases occurring for patients in areas where few alternatives remain. Given the preferences patients reveal for proximity when choosing a nursing home, these results imply a substantial welfare loss for displaced patients even independent of the mortality results. However, informational frictions in this market make it difficult to assess whether this reduction in access should outweigh any mortality improvements, an issue I explore in Section 4.5.

14. For instance, Gandhi (2020) estimates an average demand elasticity with respect to distance of 4.15%, and an average demand elasticity with respect to quality of only 0.59%.

15. I recover this from the Medicare enrollment records. Specifically, I pull the last observed zip code prior to the patient's first nursing home assessment in the MDS. Prior to 2010, the MDS also reported each resident's home zip code; I use this variable for patients whose stays began prior to 2000.

Turning to the mechanisms behind the mortality results, I consider two primary measures of nursing home quality to examine the role of patient reallocation in driving the long-run mortality reductions. First, relying on the results of annual inspections for the universe of certified facilities, I consider the number of 'quality-of-care' deficiency citations each facility earns. These citations correspond to care-related violations (such as nursing, rehabilitation, or pharmacy) rather than, for instance, fire safety infractions. By construction, patients who do not transfer to a new facility are excluded from these analyses. To ensure compatibility in the measures across time, I fix the deficiency counts at their levels prior to the closure. Because these data extend back only to 2006, I restrict the sample to only those closures occurring after this date.

These results, documented in Figure 7 panel (c), indicate that when residents transfer, they move to facilities with substantially fewer deficiency citations. The number of care citations in the facility to which a patient transfers is 29.5% lower than the closing facility. Similarly, patients experience identical declines in the number of severe deficiencies indicating actual patient harm or immediate jeopardy, as well as among total deficiencies (Appendix Figure D.15). To ease the comparison between residents in different areas, I add the baseline means of each variable to their corresponding β^{τ} coefficients. Residents in competitive areas tended to be in facilities with higher baseline rates, and they also experienced larger quality improvement, relative to their base levels. Relative to patients' new facilities, closing facilities are more likely to have any citations, and to be in the tail end of the quality distribution (Appendix Figure D.16). These results are consistent with the mortality results indicating clinically meaningful benefits from patient reallocation.

I also construct an alternative measure of nursing home quality using risk-adjusted facility 90-day survival. This is a common approach to measuring health care provider quality (Doyle Jr et al. 2015; Chandra et al. 2016; Cheng 2023). While this measure may have more limited relevance to the long-stay population that I study (who, by construction, have survived more than 90 days after admission), this measure is likely to be correlated with other notions of quality that likely matter for long-stay residents. Appendix C provides a discussion of how this alternative quality measure is constructed. Examining reallocation with this measure of quality, I find consistent results in Figure 7 panel (d). Exiting facilities tend to have lower survival rates compared to receiving facilities, and patients experience a corresponding improvement in the quality of care they experience.

There is considerable herding in patients' choice of new facility. 37.1% of displaced patients that appear in a new facility move to the most common receiving facility for their closure (i.e., the nursing home that absorbed the most patients from that closing facility). 52.2% transfer to one of the top two choices (Appendix Figure D.17). This high share is unsurprising: patient preferences over facilities are likely to be correlated, and the closing facility may play a large role in facilitating these moves. Facilities that absorb many patients (i.e., those that are among the top two largest recipients of displaced patients) see a permanent increase in their patient volume. The number of quarterly residents served at one of these facilities increases 6.0% in the quarter of the closure, and remains elevated in all subsequent quarters (Appendix Figure D.18).

To understand the role of facility quality and reallocation in mediating the overall patient survival effects documented in Figure 3, I re-estimate equation (1), subsetting to different groups of patients based on the risk-adjusted survival of their original and expected destination facilities.[16] The results are presented in Figure 8. In the top panel, I find that patients whose origin facility (i.e., the closing facility) was above-median quality experience larger long-run survival improvements than those whose origin facility was low-quality. Next, I consider patients' *expected* destination facility quality, which is the average destination-facility quality that residents of facility j transfer to, weighted by the share of j's residents who transfer to each facility — leveraging the 'herding' described above.[17] Patients whose expected destination facility is high-quality experience larger long-run survival improvements than those whose expected destination facility is low-quality. Finally, in the bottom panel, I examine results by the *change* in quality, which is defined as the difference between expected destination and origin quality. Patients who experience the largest improvements in quality experience long-run survival gains; those with the smallest improvements (or declines) in quality experience no such gains. These results suggest that the long-run survival improvements are driven by patient reallocation to higher-quality facilities, and that the quality of the receiving facility plays a key role in mediating the long-run survival effects.

4.4 Hospitalizations

The sharp increase in mortality risk following nursing home closure raises the question of what drives the increase. For instance, patients may face greater risk of neglect as the facility undergoes the closure process (as staff leave), and risk medical conditions such as developing pressure ulcers or falling. To learn about the procedures that go into place during the period of the closure – including changes in facility quality during the final weeks of a facility's life as well as the risks associated with transfers to new firms, for patients who do so – I examine changes in hospitalization risk.

To examine changes in overall hospitalization risk, I estimate an analog of equation (1), replacing the dependent variable with a hospitalization indicator. I also investigate the 'potentially avoidable hospitalizations' described in Section 3.3 indicative of low-quality nursing home care. These results, presented in Figure 9, reveal a substantial increase in the risk of any hospitalization following facility exit: residents face a short-run 2.81 percentage point increase in the risk of any hospitalization. Restricting to the subset of 'preventable' hospitalizations among long-stay nursing home residents (Walsh et al. 2012), I estimate a 1.10 percentage point increase in the risk of any preventable hospitalization. This corresponds to a consistent 23% relative increase across diagnosis groups, including infections, falls/injuries, and bed sores (Table 3). Hospitalization risk eventually returns closer to its baseline rate, though remains slightly elevated. These results are consistent with declines in facility quality during the period of the closure, in addition to the potential risks inherent to transfers in this population.

16. I rely on the risk-adjusted survival measure for this exercise as the deficiencies data extend back only to 2006.

17. Here I construct an expected quality measure, rather than *realized* destination facility quality, as doing so would condition on the dependent variable (survival).

I also examine in-hospital deaths with a variety of different conditions, which I use to approximate cause-of-death as this is not recorded in the MDS (Table 3). I find that about a third of the short-run mortality effect is driven by deaths in the hospital. Of these deaths, the largest short-run increases (relative to their baseline rates) are for patients who die with infectious/parasitic diseases (208.1%) and endocrinological, nutritional, and metabolic diseases (227.5%). These rates return to their baseline levels in the long-run. The prevalence of these conditions are consistent with the provision of inadequate nursing care during the period of the closure.

4.5 Discussion and Limitations

This paper examines the impact of disruptive nursing home closures on the health of current residents. However, this focus on the mortality effects for incumbent long-stayers provides only a partial view of the total welfare implications of the wave of closures characterized in Section 2.1. In this section, I discuss some limitations and welfare implications of my results, and suggest directions for future research.

First, it should be noted that the welfare implications of these results vary meaningfully across patient types. The results in Figure 3 indicate that relatively sicker patients experience very sharp increases in mortality, while relatively healthier patients face much lower changes in their risk. Moreover, to the extent that any patients enjoy the gains of reallocation to higher quality facilities, such gains accrue (by definition) only to those fortunate enough to survive the initial disruption, who are disproportionately healthy at baseline.

Second, by focusing on long-stay residents, the analysis necessarily constrains welfare implications to a minority of the nursing home population. While economically significant, long-stay residents represent only approximately 27% of stays during the sample period. The majority of nursing home patients are short-stay residents, whose care primarily centers on rehabilitation and discharge back to the community. While my results suggest that quality is likely to improve for these residents, the research design is not well-tailored to estimate direct effects on this population. These residents likely face distinct risks and benefits from facility closures. Exploring the implications of closures for short-stay patients represents an important avenue for future research.

In addition, while this paper examines the incumbent resident population, nursing home closures have implications for future patients as well, who would have entered the facility had it remained open. By definition, prospective patients are not exposed to the disruption and transfer risk that incumbent patients face. As a result, the long-run survival gains I estimate for incumbents likely *understate* the health improvements for prospective patients, who only enjoy the survival benefits of receiving care at a higher quality facility with no short-run elevated mortality risk from the disruption, assuming they are not deterred from seeking nursing home care altogether.

Finally, for all nursing home patients (both incumbent and prospective), the total welfare implications of closures are ambiguous. My results suggest improvements in mortality and observable measures of quality, but these may not be the sole determinants of patient welfare in the nursing home context. Patients likely value having access to nearby care, and may rationally prefer to attend a closer facility over a higher quality one. This is particularly true for long-stay patients, for whom the benefits of frequent visitation from friends and family are well-documented (Greene and Monahan 1982; Port et al. 2001; Gaugler 2005). Indeed, by revealed choice nursing home residents seem to express strong preferences for proximity over facility quality. Both Hackmann (2019) and Gandhi (2020) estimate nursing home preferences using discrete choice models and find that the taste for distance far exceeds the taste for quality. Taking these revealed preferences seriously suggests that the substantial geographic displacement I find in Figure 7 panel (b) generates considerable welfare losses for prospective patients that may exceed any gains from quality improvements. This reduction in consumer surplus from changes in the choice set (i.e., fewer nearby facilities) could plausibly outweigh the gains from the survival improvements I document.

Quantifying this consumer surplus channel — and balancing it against improvements in survival — is econometrically challenging. It is possible (and perhaps likely) that other factors influence patients' actions, driving a wedge between their choices and their preferences. For example, patients may struggle to discern facility quality, leading them to choose lower quality facilities even when they would prefer higher quality.[18] Indeed, patients may be unaware of the existence of more distant facilities, which would also tend to inflate estimates of the taste for distance. Similarly, empirical estimates of high demand elasticities with respect to distance may partially reflect the preferences of other surrogates in the decision-making process (such as adult children who have a distaste for driving longer distances) who may play a large role in choosing a facility. In this case, the loss in consumer surplus derived from empirical demand estimates may overstate the welfare loss of a closure, if patients' "true" preferences do not reflect such a strong taste for proximity. For these reasons, I do not attempt to quantify the total welfare implications of nursing home closures in this paper, but instead focus on the health impacts for the incumbent population. How to best weigh these competing considerations is an important question for future research.

5 Conclusion

This paper examines the disruption and displacement impacts of the recent wave of nursing home closures on incumbent residents. Nursing home closures likely entail short-run risks for displaced residents but may also generate longer-term benefits if residents transfer to higher quality firms. Measuring both effects is crucial for understanding the implications of the ongoing contraction in the nursing home industry.

I find consistent evidence of substantial short-run mortality costs following closure, particularly for residents with higher acuity levels. Surviving residents tend to transfer to higher-quality facilities, and I find suggestive evidence of longer-run survival gains — primarily for younger and healthier patients. Geographic heterogeneity, in particular by local market conditions, suggests that the costs are highest in areas with less competition, whereas any gains accrue only to patients in robust nursing home markets.

18. Recent work by Cheng (2023) suggests that information frictions play a considerable role in nursing home choice.

The findings of this paper underscore the need to mitigate the immediate mortality risks associated with nursing home closures, particularly for older and sicker residents who are disproportionately affected. It is notable that even though there is some anticipation of these closures (e.g., there is evidence that patients begin to transfer out in the prior quarter), the processes nevertheless result in such poor outcomes. Standardized protocols for managing closures, such as robust relocation support for residents and their families, as well as longer advance notice periods above the common 60-day window may help mitigate the short-run mortality effects I document. Similarly, targeted investments in transition assistance — such as expanding case management services, close monitoring of patient health during transitions, and ensuring continuity of care — could alleviate the disruption experienced by residents during relocations. For markets with limited provider competition, where reallocation may not naturally lead to improved outcomes, policies should focus on fostering new provider entry or incentivizing quality improvements among existing facilities (for example, Gandhi et al. (2024) provide evidence that incentive payments effectively raised quality even for Medicaid-focused firms at relatively greater risk of closure). Finally, the evidence that short-term mortality costs are not offset for certain subgroups highlights the importance of tailoring interventions to patient-specific needs, such as providing specialized support for dementia patients or frail elderly residents. Such actions may help to safeguard vulnerable populations while maintaining access to high-quality care in a rapidly changing nursing home market.

References

Abadie, Alberto, Susan Athey, Guido W Imbens, and Jeffrey M Wooldridge. 2023. "When should you adjust standard errors for clustering?" *The Quarterly Journal of Economics* 138 (1): 1–35.

AHCA. 2018. *A Report on Shortfalls in Medicaid Funding for Nursing Center Care.* Technical report. American Health Care Association.

Antill, Samuel, Jessica Bai, Ashvin Gandhi, and Adrienne Sabety. 2025. "Healthcare Provider Bankruptcies." NBER Working Paper No. 33763.

Arrow, Kenneth. 1963. "Uncertainty and the Welfare Economics of Medical Care." *American Economic Review* 53 (5): 33.

Battaglia, Emily. 2022. *The Effect of Hospital Closures on Maternal and Infant Health.* Working Paper. Unpublished.

California State Legislature. 2020. *California Health and Safety Code Section 1569.682.* https://leginfo.legislature.ca.gov/faces/codes_displaySection.xhtml?sectionNum=1569.682.&lawCode=HSC. Amended by Stats. 2020, Ch. 11, Sec. 11 (AB 79), Effective June 29, 2020.

Carroll, Caitlin. 2019. *Impeding Access or Promoting Efficiency? Effects of Rural Hospital Closure on the Cost and Quality of Care.* Working Paper. Unpublished.

Castle, Nicholas G, and John B Engberg. 2011. "The health consequences of relocation for nursing home residents following Hurricane Katrina." *Research on Aging* 33 (6): 661–687.

Castle, Nicholas G., John Engberg, Judith Lave, and Andrew Fisher. 2009. "Factors Associated with Increasing Nursing Home Closures." *Health Services Research* 44 (3): 1088–1109.

Centers for Medicare & Medicaid Services. 2022. *Medicaid and CHIP Expenditures by Service Category.* Online dataset published by Medicaid.gov.

Chandra, Amitabh, Amy Finkelstein, Adam Sacarny, and Chad Syverson. 2016. "Health Care Exceptionalism? Performance and Allocation in the US Health Care Sector." *American Economic Review* 106 (8): 2110–2144.

Cheng, Alden. 2023. "Demand for Quality in the Presence of Information Frictions: Evidence from the Nursing Home Market." Working Paper.

Ching, Andrew T., Fumiko Hayashi, and Hui Wang. 2015. "Quantifying the Impacts of Limited Supply: The Case of Nursing Homes." *International Economic Review* 56 (4): 1291–1322.

De Loecker, Jan, and Chad Syverson. 2021. "An Industrial Organization Perspective on Productivity." In *Handbook of Industrial Organization,* edited by Kate Ho, Ali Hortaçsu, and Alessandro Lizzeri, 4:141–223. Handbook of Industrial Organization, Volume 4. Elsevier.

Deaner, Ben, and Hyejin Ku. 2024. "Causal Duration Analysis with Diff-in-Diff." *arXiv preprint arXiv:2405.05220.*

Deryugina, Tatyana, and David Molitor. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review* 110 (11): 3602–3633.

Doyle Jr, Joseph J, John A Graves, Jonathan Gruber, and Samuel A Kleiner. 2015. "Measuring returns to hospital care: Evidence from ambulance referral patterns." *Journal of Political Economy* 123 (1): 170–214.

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2022. "Producing Health: Measuring Value Added of Nursing Homes." NBER Working Paper No. 30228.

Falk, Hanna, Helle Wijk, and Lars-Olof Persson. 2011. "Frail older persons' experiences of interinstitutional relocation." *Geriatric Nursing* 32 (4): 245–256.

Fischer, Stefanie, Heather Royer, and Corey White. 2024. "Health Care Centralization: The Health Impacts of Obstetric Unit Closures in the United States." *American Economic Journal: Applied Economics* 16 (3): 113–141.

Foster, Lucia, John Haltiwanger, and C. J Krizan. 2006. "Market Selection, Reallocation, and Restructuring in the U.S. Retail Trade Sector in the 1990s." *Review of Economics and Statistics* 88 (4): 748–758.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98 (1): 394–425.

Gandhi, Ashvin. 2020. *Picking Your Patients: Selective Admissions in the Nursing Home Industry.* Working Paper. Unpublished.

Gandhi, Ashvin, and Andrew Olenski. 2024. "Tunneling and Hidden Profits in Health Care." NBER Working Paper No. 32258.

Gandhi, Ashvin, YoungJun Song, and Prabhava Upadrashta. 2020. *Private Equity, Consumers, and Competition: Evidence from the Nursing Home Industry.* Working Paper. Unpublished.

Gandhi, Ashvin D., Andrew Olenski, Krista Ruffini, and Karen Shen. 2024. "Alleviating Worker Shortages Through Targeted Subsidies: Evidence from Incentive Payments in Healthcare." *The Review of Economics and Statistics,* 1–31.

Gaugler, J. E. 2005. "Family Involvement in Residential Long-Term Care: A Synthesis and Critical Review." *Aging & Mental Health* 9 (2): 105–118.

Geng, Fangli, David G. Stevenson, and David C. Grabowski. 2019. "Daily Nursing Home Staffing Levels Highly Variable, Often Below CMS Expectations." *Health Affairs* 38 (7): 1095–1100.

Grabowski, David C., Jonathan Gruber, and Joseph J. Angelelli. 2008. "Nursing Home Quality as a Common Good." *The Review of Economics and Statistics* 90 (4): 754–764.

Grabowski, David C., and David G. Stevenson. 2008. "Ownership Conversions and Nursing Home Performance." *Health Services Research* 43 (4): 1184–1203.

Greene, V. L., and D. J. Monahan. 1982. "The Impact of Visitation on Patient Well-Being in Nursing Homes." *The Gerontologist* 22 (4): 418–423.

Gupta, Atul, Sabrina T Howell, Constantine Yannelis, and Abhinav Gupta. 2023. "Owner Incentives and Performance in Healthcare: Private Equity Investment in Nursing Homes." *The Review of Financial Studies* 37 (4): 1029–1077.

Hackmann, Martin B. 2019. "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry." *American Economic Review* 109 (5): 1684–1716.

Hackmann, Martin B., R. Vincent Pohl, and Nicolas R. Ziebarth. 2024. "Patient versus Provider Incentives in Long-Term Care." *American Economic Journal: Applied Economics* 16 (3): 178–218.

Harrington, Charlene, Helen Carrillo, Rachel Garfield, and Ellen Squires. 2018. *Nursing Facilities, Staffing, Residents and Facility Deficiencies, 2009 Through 2016.*

Harrington, Charlene, John F. Schnelle, Margaret McGregor, and Sandra F. Simmons. 2016. "The Need for Higher Minimum Staffing Standards in U.S. Nursing Homes." *Health Services Insights* 9:13–19.

Healy, Jack. 2019. "Nursing Homes Are Closing Across Rural America, Scattering Residents." *The New York Times.*

Holder, Jacquetta M, and David Jolley. 2012. "Forced relocation between nursing homes: residents' health outcomes and potential moderators." *Reviews in Clinical Gerontology* 22 (4): 301–319.

Huang, Sean Shenghsiu, and John R. Bowblis. 2019. "Private Equity Ownership and Nursing Home Quality: An Instrumental Variables Approach." *International Journal of Health Economics and Management* 19 (3-4): 273–299.

Institute of Medicine. 1986. *Improving the Quality of Care in Nursing Homes.* Washington (DC): National Academies Press (US).

Joynt, Karen E., Paula Chatterjee, E. John Orav, and Ashish K. Jha. 2015. "Hospital Closures Had No Measurable Impact On Local Hospitalization Rates Or Mortality Rates, 2003–11." *Health Affairs* 34 (5): 765–772.

Kwok, Jennifer H. 2019. *How Do Primary Care Physicians Influence Healthcare?* Working Paper. Unpublished.

Laughlin, Ann, Mary Parsons, Karl D Kosloski, and Brenda Bergman-Evans. 2007. "Predictors of mortality following involuntary interinstitutional relocation." *Journal of Gerontological Nursing* 33 (9).

Levere, Michael, Patricia Rowan, and Andrea Wysocki. 2021. "The Adverse Effects of the COVID-19 Pandemic on Nursing Home Resident Well-Being." *Journal of the American Medical Directors Association* 22 (5): 948–954.e2.

Lin, Haizhen. 2015. "Quality Choice and Market Structure: A Dynamic Analysis of Nursing Home Oligopolies." *International Economic Review* 56 (4): 1261–1290.

Meehan, Tom, Tom Meehan, Samantha Robertson, Terry Stedman, and Gerard Byrne. 2004. "Outcomes for elderly patients with mental illness following relocation from a stand-alone psychiatric hospital to community-based extended care units." *Australian & New Zealand Journal of Psychiatry* 38 (11-12): 948–952.

Mirotznik, Jerrold, and Lenore Los Kamp. 2000. "Cognitive status and relocation stress: A test of the vulnerability hypothesis." *The Gerontologist* 40 (5): 531–539.

Office of Inspector General. 2014. *Adverse Events in Skilled Nursing Facilities: National Incidence Among Medicare Beneficiaries.* Technical report. Department of Health and Human Services.

Olenski, Andrew, and Szymon Sacher. 2022. *Estimating Nursing Home Quality with Selection.* Working Paper. Unpublished.

Olley, G. Steven, and Ariel Pakes. 1996. "The Dynamics of Productivity in the Telecommunications Equipment Industry." *Econometrica* 64 (6): 1263–1297.

Port, C. L., A. L. Gruber-Baldini, L. Burton, M. Baumgarten, J. R. Hebel, S. I. Zimmerman, and J. Magaziner. 2001. "Resident Contact with Family and Friends Following Nursing Home Admission." *The Gerontologist* 41 (5): 589–596.

Sabety, Adrienne. 2023. "The Value of Relationships in Healthcare." *Journal of Public Economics* 225:104927.

Saslow, Eli. 2019. "Traveling the Loneliest Road." *Washington Post.*

Schwab, Stephen D. 2021. *The Value of Specific Information: Evidence from Disruptions to the Patient- Physician Relationship.* Working Paper. Unpublished.

Silver-Greenberg, Jessica, and Robert Gebeloff. 2021. "Maggots, Rape and Yet Five Stars: How U.S. Ratings of Nursing Homes Mislead the Public." *The New York Times.*

Stall, Nathan M., Jonathan S. Zipursky, Jagadish Rangrej, Aaron Jones, Andrew P. Costa, Michael P. Hillmer, and Kevin Brown. 2021. "Assessment of Psychotropic Drug Prescribing Among Nursing Home Residents in Ontario, Canada, During the COVID-19 Pandemic." *JAMA Internal Medicine.*

Syverson, Chad. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49 (2): 326–365.

Templeton, Zachary S, Nate C Apathy, R Tamara Konetzka, Meghan M Skira, and Rachel M Werner. 2023. "The Health Effects of Nursing Home Specialization in Post-Acute Care." *Journal of Health Economics* 92:102823.

Thomas, Katie. 2014. "Medicare Star Ratings Allow Nursing Homes to Game the System." *The New York Times.*

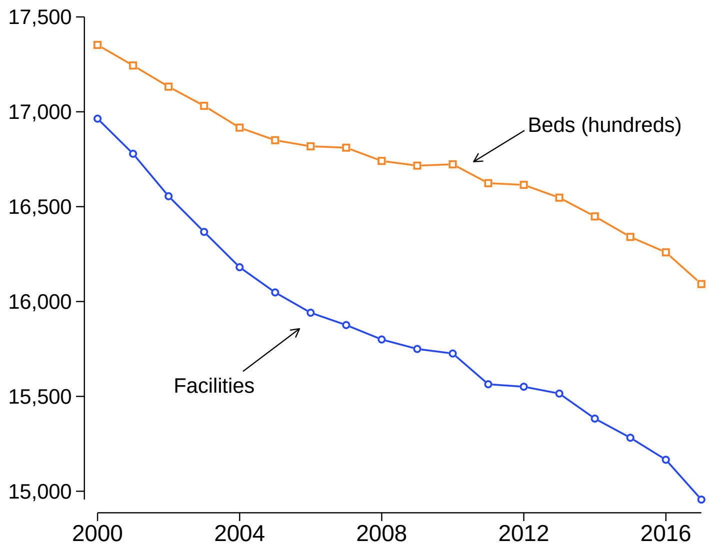
Thorson, James A, and Ruth Ellen Davis. 2000. "Relocation of the institutionalized aged." *Journal of Clinical Psychology* 56 (1): 131–138.

Walsh, Edith G., Joshua M. Wiener, Susan Haber, Arnold Bragg, Marc Freiman, and Joseph G. Ouslander. 2012. "Potentially Avoidable Hospitalizations of Dually Eligible Medicare and Medicaid Beneficiaries from Nursing Facility and Home- and Community-Based Services Waiver Programs." *Journal of the American Geriatrics Society* 60 (5): 821–829.

Zinn, Jacqueline, Vincent Mor, Zhanlian Feng, and Orna Intrator. 2009. "Determinants of Performance Failure in the Nursing Home Industry." *Social Science & Medicine* 68 (5): 933–940.

6 Tables and Figures

(a) Aggregate Nursing Home Reduction



(b) Geographic Variation in Capacity Decline

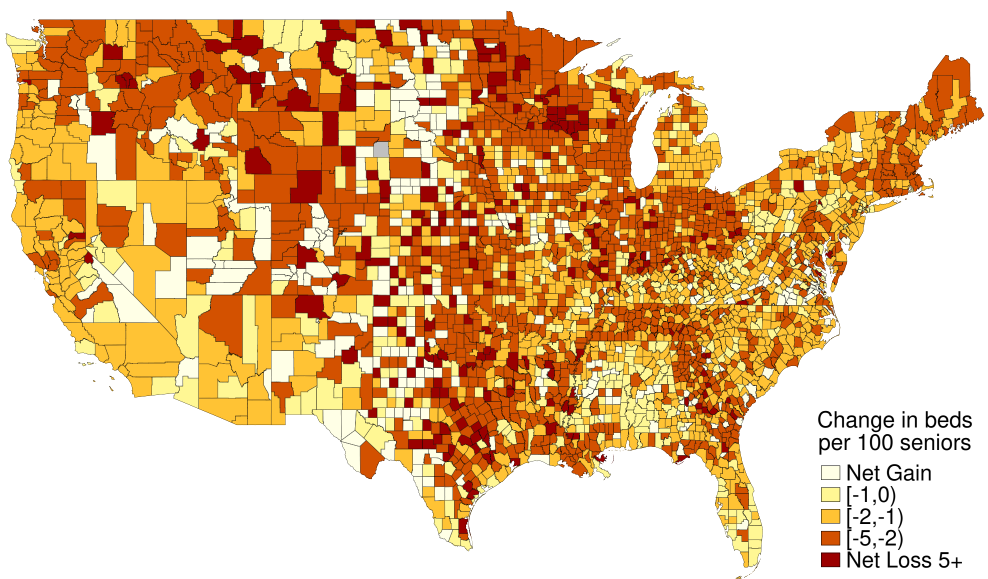


Figure 1: Contraction in the Nursing Home Industry

Notes: Top panel documents the decline in the total number of skilled nursing facilities and beds over the period 2000-2017. Bed counts are measured in hundreds on the same axis. Bottom panel documents the (county-level) geographic variation in the decline of nursing home capacity over the sample period, with the sharpest reductions occurring in rural areas in the South and Midwest. Data from the LTCFocus.org database and the U.S. Census Bureau annual population estimates.

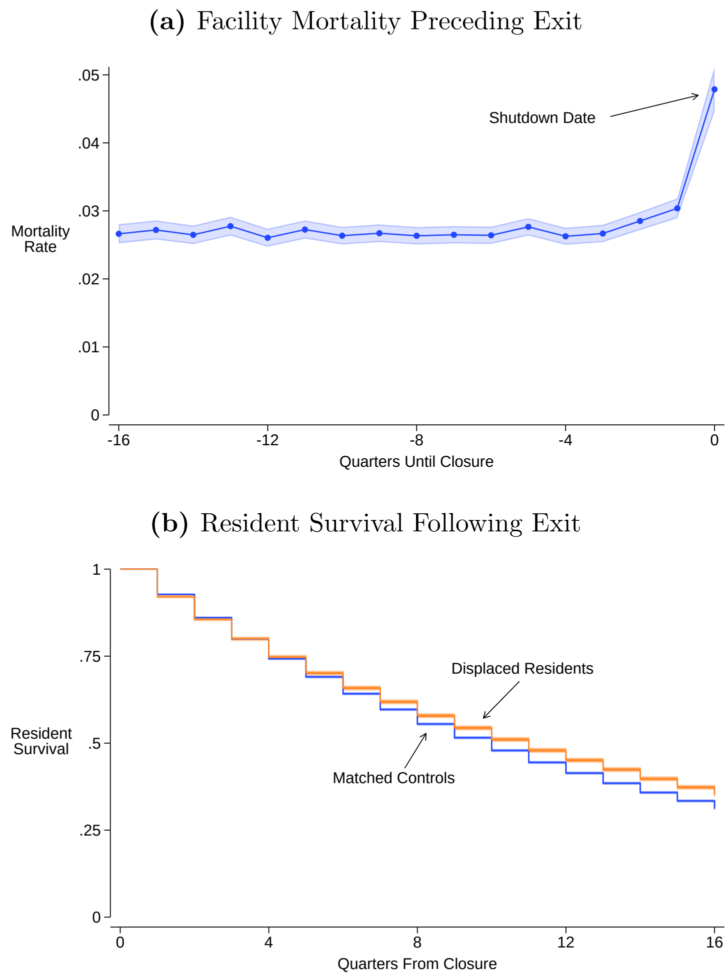


Figure 2: Preliminary Evidence on Mortality Effects of Nursing Home Exits

Notes: Figures present preliminary empirical patterns on the relationship between nursing facility shutdown and resident mortality. Panel (a) documents the mean facility-level quarterly mortality rate in the four years preceding the exit, including the spike at the time of closure. Panel (b) tracks the survival rates of residents displaced by the exits, relative to a matched control sample of residents in facilities that did not exit. The matching is described in Section 3. All error bands indicate 95% pointwise confidence intervals.

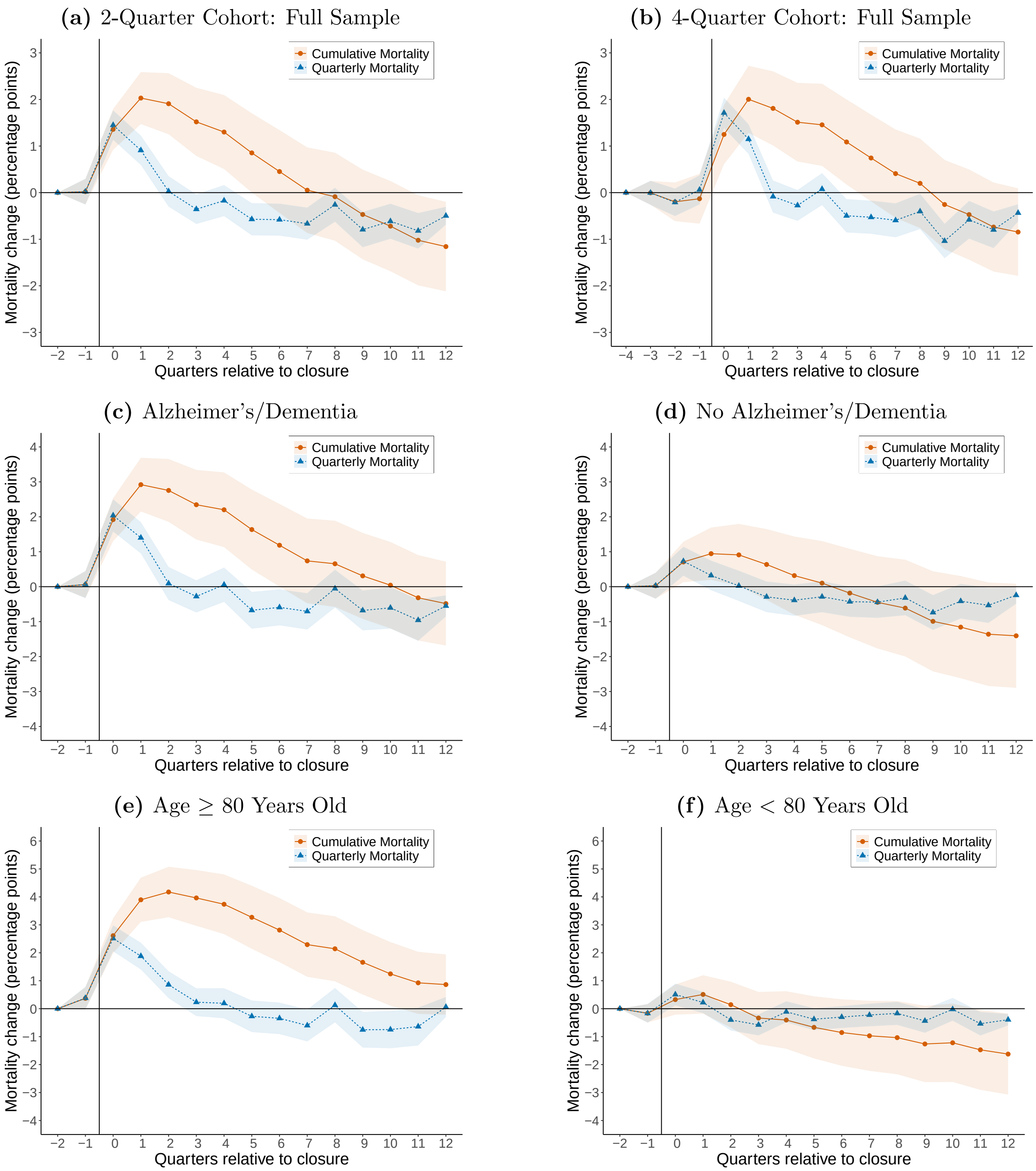


Figure 3: Mortality effects of nursing home exit on current residents

Notes: Figures present the results from estimating equation (1). The quarterly mortality estimates (the β^τ coefficients) capture the per-period change in mortality probability, conditional on surviving to quarter t. The cumulative mortality estimates (ΔM_t) capture the cumulative effect on the baseline cohort up to period t. Panel (a) presents the results for the main cohort, those present in a closing nursing home two quarters prior to exit. Panel (b) presents results for the robustness cohort, those present four quarters prior to exit, allowing for comparison of parallel trends between the treatment and control groups. Panels (c) and (d) present results from the main cohort, by Alzheimer's/dementia status. Panels (e) and (f) present results from the main cohort, by age. All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported.

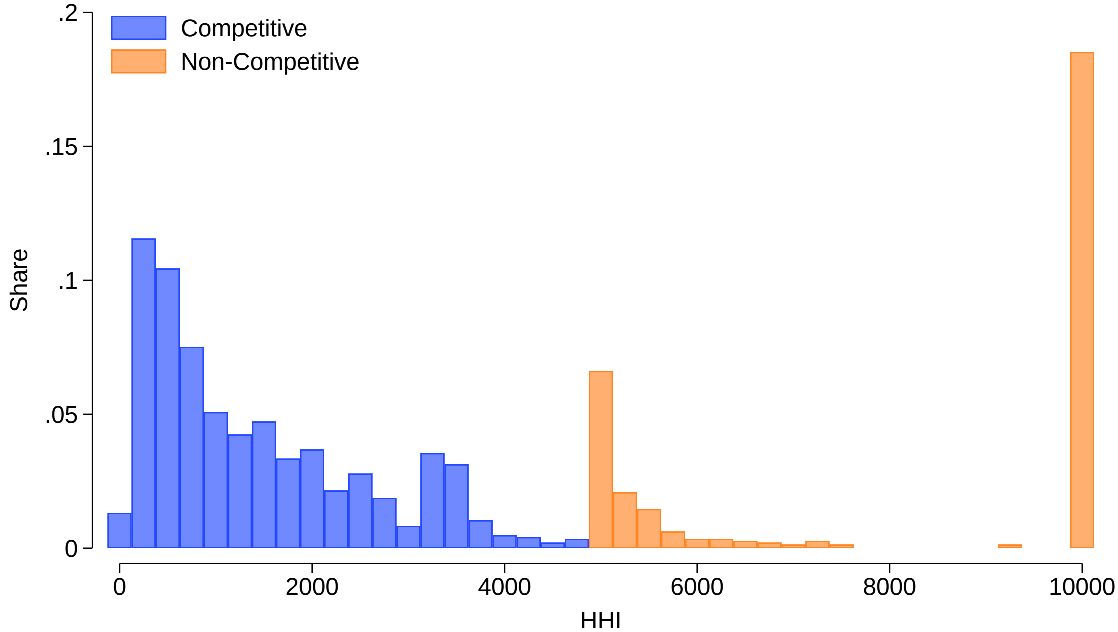


Figure 4: Distribution of HHI in year prior to exit among analysis sample

Notes: Figure plots the distribution of facility-level Hirschman-Herfindahl Index (HHI), drawn using a 10 kilometer radius around each facility. HHI is defined over facility capacity (number of beds) in the year prior to the closure. Facilities that are at least duopolists in this market definition (HHI$\geq 5,000$) are defined as non-competitive, and the remainder as competitive.

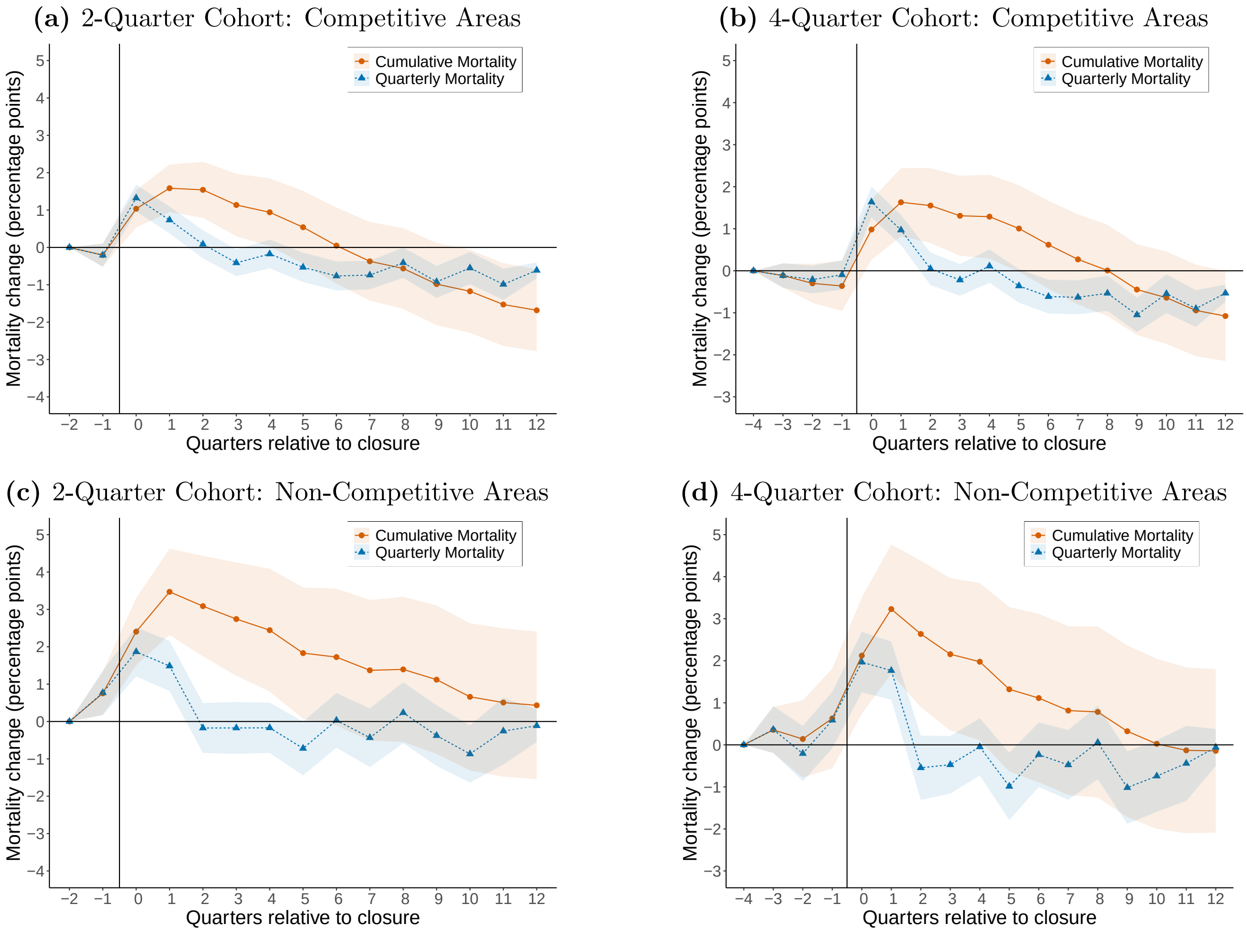


Figure 5: Mortality effects by market competition

Notes: Figures present the results from estimating equation (1). The quarterly mortality estimates (the β^{τ} coefficients) capture the per-period change in mortality probability, conditional on surviving to quarter t. The cumulative mortality estimates (ΔM_t) capture the cumulative effect on the baseline cohort up to period t. Figures on the left present results for the main cohort, those present in a closing nursing home two quarters prior to exit. Figures on the right present results for the robustness cohort, those present four quarters prior to exit, allowing for comparison of parallel trends between the treatment and control groups. Panels (a) and (b) contain results for residents of facilities in competitive markets (pre-closure HHI below 5,000). Panels (c) and (d) presents results for residents of facilities in non-competitive markets (pre-closure HHI above 5,000). All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported.

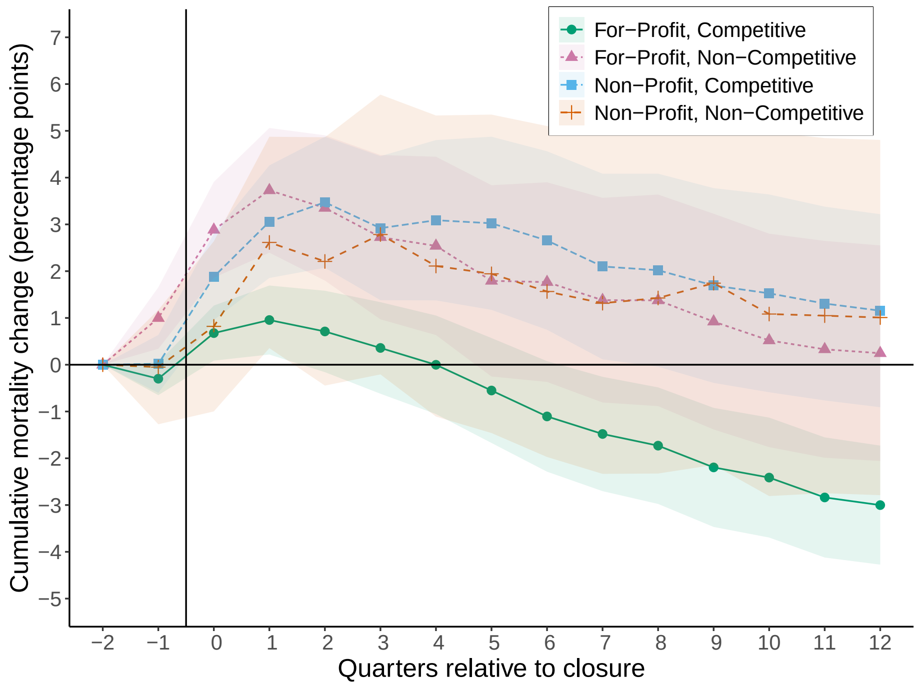


Figure 6: Cumulative mortality by concentration and ownership status

Notes: Figure plots the cumulative mortality effects from equation (2), omitting the quarterly mortality estimates β^τ for clarity. Each ΔM_t series represents estimates from a different subgroup, segmented by the intersections of concentration and ownership status. All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported. These groups are mutually exclusive, comprising the following shares of all closures in the sample: competitive, for-profit (50.4%), non-competitive, for-profit (23.3%), competitive, non-profit (19.4%), and non-competitive, non-profit (6.9%).

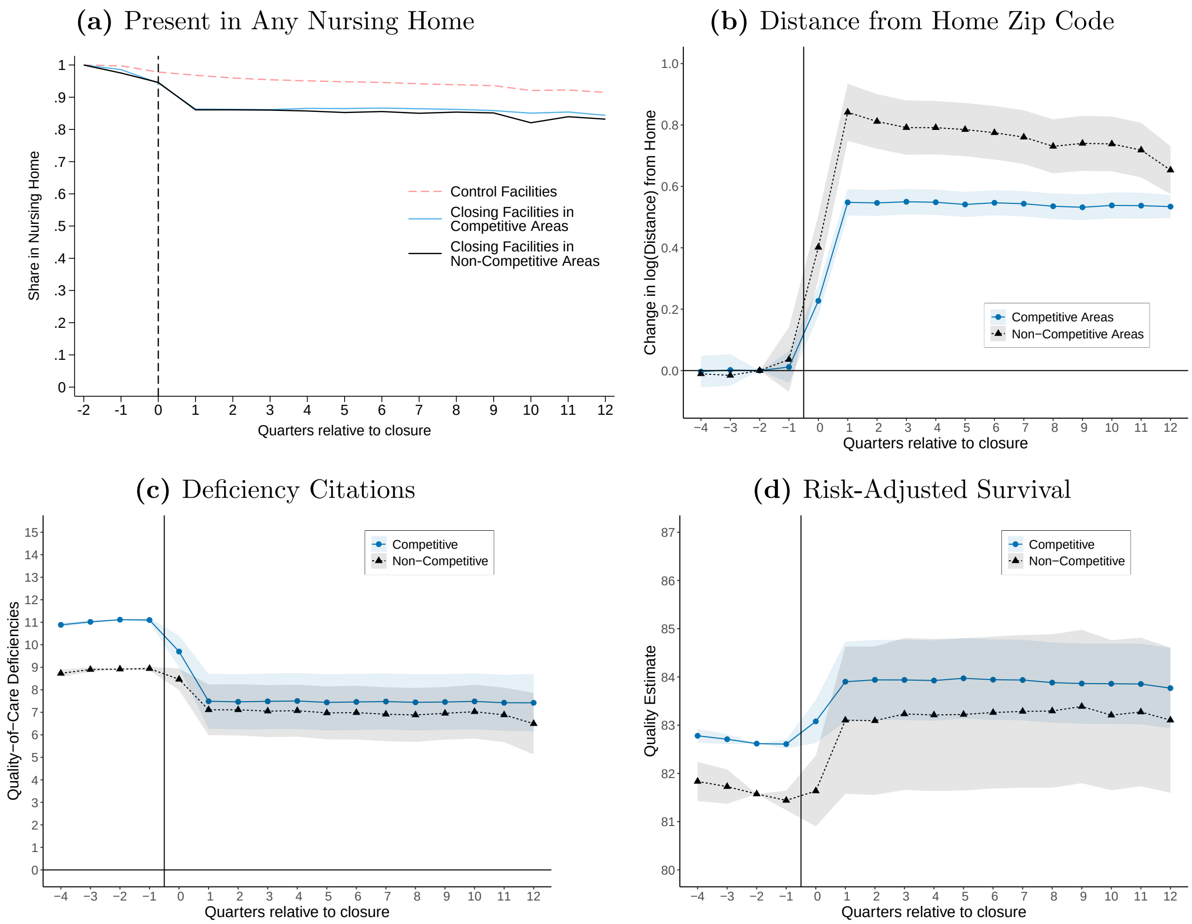


Figure 7: Reallocation to New Facilities

Notes: Figures present how patients reallocate following their displacement from a closing nursing home. Panel (a) shows the share of residents present in any nursing home in a given quarter. The remaining panels investigate characteristics of residents' new facilities, presenting estimates of β^{τ} from equation (1), with the dependent variable replaced with a measure of facility quality. Panel (b) plots how far patients are displaced following their nursing home closure. Distance is determined using the resident's last 5-digit zip code (from the Medicare enrollment records) prior to their initial nursing home stay. Panel (c) shows the reduction in the number of 'quality-of-care' deficiencies. Panel (d) plots the risk-adjusted survival rate of the resident's current facility, an alternative measure of quality. Heterogeneous effects are estimated jointly, interacting the concentration measure with the relative time indicators. Patients who do not transfer to a new nursing home are excluded.

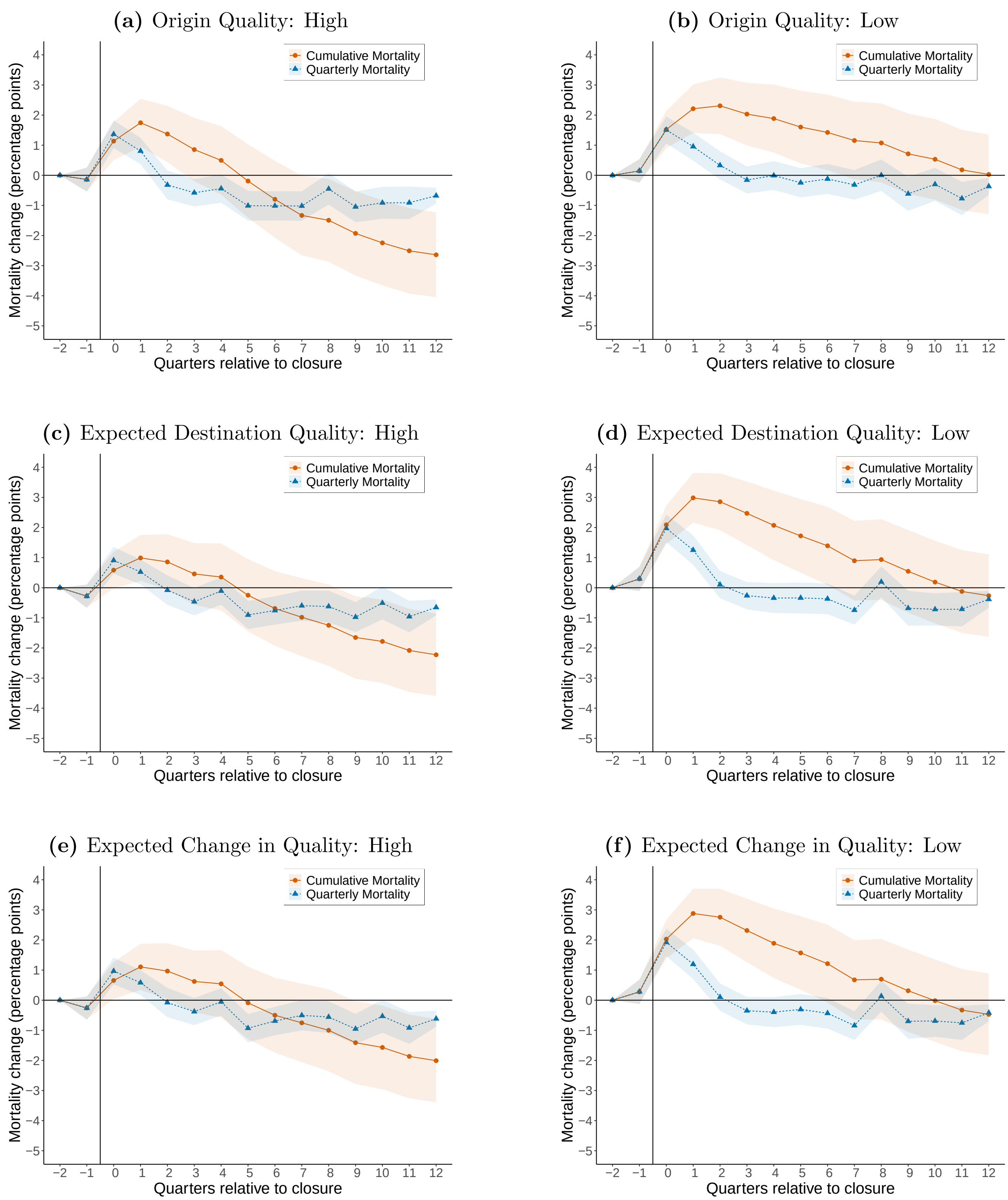
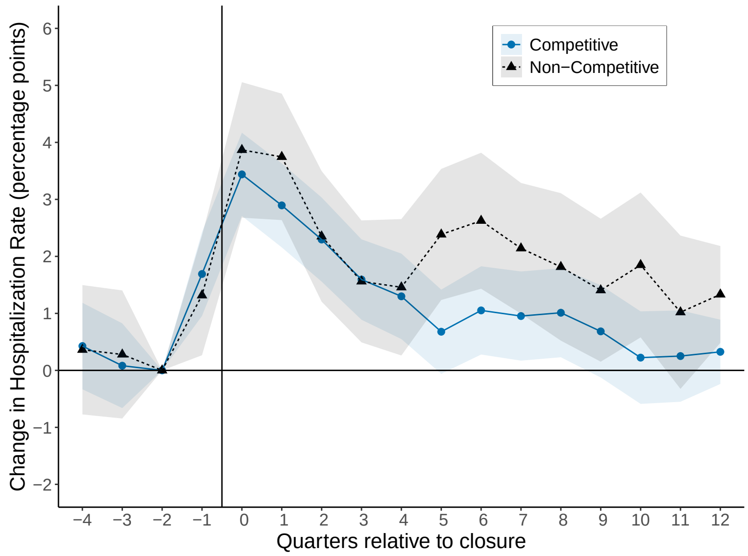


Figure 8: Mortality effects stratified by facility quality

Notes: Figures present results from estimating equation (1). The quarterly mortality estimates (β^τ coefficients) capture the per-period change in mortality probability, conditional on surviving to quarter t. The cumulative mortality estimates (ΔM_t) capture the cumulative effect on the baseline cohort up to period t. Panels are stratified as follows: Top row shows origin facility quality, middle row shows expected destination facility quality, bottom row shows change in quality between origin and expected destination facilities.

(a) Hospitalization Rate



(b) Potentially Avoidable Hospitalization Rate

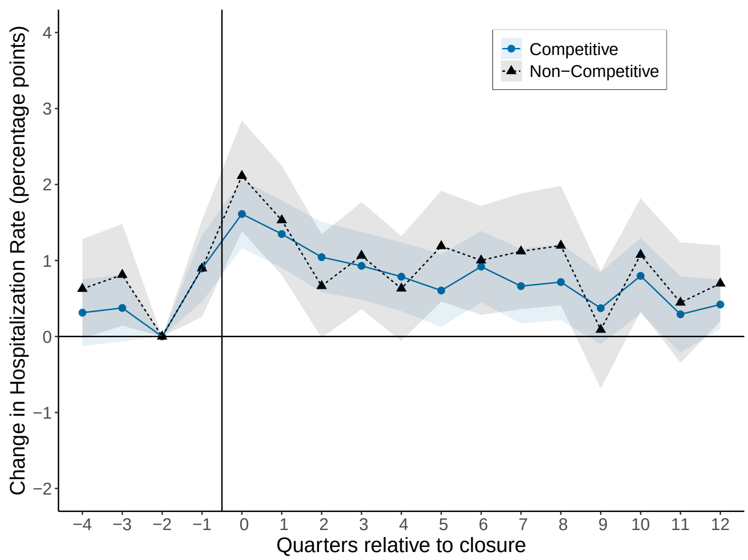


Figure 9: Hospitalization Results

Notes: Figure presents the results from estimating equation (1) using the baseline resident cohort. In both panels the dependent variable is an indicator for a short-stay hospitalization in the quarter. The top panel corresponds to any acute care stay. The bottom panel corresponds to a 'potentially avoidable hospitalization,' reflective of low quality of nursing home care. All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported.

	Closing Facility (1)	Matched Facility (2)
Resident Characteristics		
White, %	78.7 (40.9)	80.4 (39.7)
Female %	66.0 (47.4)	70.1 (45.8)
Age	78.8 (13.2)	80.9 (12.0)
Medicare Advantage %	12.6 (33.2)	11.9 (32.3)
Prior Diagnoses		
Diabetes, %	30.8 (46.1)	31.3 (46.4)
Peripheral Vascular Disease, %	13.6 (34.3)	14.7 (35.4)
Alzheimer's/Dementia, %	55.9 (49.6)	57.2 (49.5)
Stroke, %	23.7 (42.5)	25.9 (43.8)
Depression, %	52.2 (50.0)	53.5 (49.9)
Hip Fracture, %	7.9 (27.0)	9.2 (28.9)
Requires Assistance		
Toileting, %	70.5 (45.6)	72.8 (44.5)
Dressing, %	71.7 (45.1)	73.3 (44.2)
Eating, %	32.5 (46.8)	32.5 (46.8)
Hygiene, %	72.4 (44.7)	72.8 (44.5)
Transfers, %	61.5 (48.7)	65.3 (47.6)
Baseline Mortality Rate, %	7.06 (25.6)	7.42 (26.2)
Number of Residents	42,942	208,553

Table 1: Summary Statistics

Notes: Table presents summary statistics for the baseline analytic sample. Standard deviations are reported in parentheses. Column (1) describes the characteristics (observed two quarters prior to closure) of the residents of closed facilities. Column (2) describes the characteristics of the residents of the matched control facilities.

	Full Sample		Competitive		Concentrated	
	(1)	(2)	(3)	(4)	(5)	(6)
β_{SR}	1.14***	1.18***	1.11***	1.14***	1.25***	1.30***
	(0.12)	(0.12)	(0.14)	(0.14)	(0.26)	(0.26)
β_{LR}	-0.55***	-0.47***	-0.51***	-0.44***	-0.67***	-0.59**
	(0.08)	(0.08)	(0.09)	(0.09)	(0.18)	(0.18)
ΔM_1	1.95***	2.03***	1.51***	1.58***	3.37***	3.47***
	(0.28)	(0.28)	(0.32)	(0.32)	(0.59)	(0.59)
ΔM_4	0.99*	1.30**	0.66	0.94*	2.03*	2.44**
	(0.40)	(0.41)	(0.46)	(0.46)	(0.83)	(0.84)
ΔM_8	-0.59	-0.09	-1.03	-0.56	0.75	1.39
	(0.48)	(0.48)	(0.54)	(0.55)	(0.99)	(0.99)
ΔM_{12}	-1.67***	-1.16*	-2.16***	-1.68**	-0.18	0.43
	(0.48)	(0.49)	(0.55)	(0.56)	(1.00)	(1.01)
N	3,603,313	3,603,313	2,826,587	2,826,587	776,726	776,726
Dep. Var Mean	6.34	6.34	6.21	6.21	6.80	6.80
Controls	Base	Full	Base	Full	Base	Full

Table 2: Short-run and Long-run Mortality Effects of Nursing Home Closures

Notes: Table summarizes the main mortality effects of nursing home closures. Top panel summarizes the mortality hazards β into short-run (weighted average of relative quarters 0-1) and long-run (weighted average of relative quarters 2+). The next panel reports the cumulative mortality effects ΔM_t at several benchmarks after closure, including one quarter, one year, two years, and three years following closure. Columns (1) and (2) report results using the full sample. Columns (3) and (4) report results restricted to residents of nursing homes that were in competitive markets prior to exit. Columns (5) and (6) report the corresponding results for concentrated markets. All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported.

	Baseline, %	Short-Run		Long-Run	
		β	Percent β	β	Percent β
	(1)	(2)	(3)	(4)	(5)
Any Hospitalization	13.15	2.81 (0.19)***	21.3 (1.4)***	0.44 (0.18)*	3.4 (1.3)*
Any Preventable Hospitalization	4.98	1.10 (0.11)***	22.1 (2.3)***	0.18 (0.09)	3.6 (1.8)
Preventable Hospitalization					
Infections	3.19	0.74 (0.09)***	23.0 (3.0)***	0.01 (0.07)	0.3 (2.3)
Falls/Injuries	1.03	0.24 (0.04)***	23.2 (4.1)***	0.14 (0.03)***	13.7 (2.7)***
Nutrition/Hydration	0.35	0.08 (0.03)**	23.8 (8.2)**	0.03 (0.02)	8.3 (5.7)
Bed Sores	0.35	0.06 (0.03)*	16.8 (8.3)*	0.00 (0.02)	0.8 (5.8)
Psychosis	0.18	0.05 (0.02)*	26.8 (11.4)*	0.00 (0.02)	1.3 (8.6)
Any In-hospital Death	0.32	0.28 (0.05)***	87.2 (15.9)***	-0.08 (0.02)**	-24.0 (7.6)**
In-hospital Death with Diagnosis					
Infectious/Parasitic Diseases	0.04	0.08 (0.02)***	208.1 (45.2)***	-0.01 (0.01)	-30.3 (26.0)
Respiratory System	0.09	0.06 (0.03)*	75.3 (29.5)*	-0.01 (0.01)	-11.2 (13.7)
Endocrine/Nutritional/Metabolic	0.01	0.02 (0.01)*	227.5 (95.2)*	0.00 (0.00)	-35.7 (41.4)
Digestive System	0.02	0.02 (0.01)	86.1 (69.2)	-0.01 (0.01)	-52.0 (30.3)
Kidney/Urinary Tract	0.02	0.02 (0.01)	78.5 (55.8)	-0.01 (0.01)	-46.2 (24.3)
Musculoskeletal	0.01	0.01 (0.01)	90.6 (90.3)	0.00 (0.00)	-16.9 (40.5)
Circulatory System	0.05	0.00 (0.02)	-5.1 (36.5)	-0.01 (0.01)	-17.2 (18.0)
Nervous System	0.02	0.00 (0.01)	25.9 (62.3)	-0.01 (0.00)*	-68.1 (29.7)*

Table 3: Hospitalization Results

Notes: Table reports the hospitalization rates for the baseline resident cohort. Each row corresponds to a different estimation of equation (1) using the dependent variable listed. Column (1) reports the control group mean at baseline. Columns (2) and (4) report the short- and long-run effects (corresponding to relative quarters 0-1 and 2+) of nursing home closure, respectively. Columns (3) and (5) scale the corresponding β point estimates by the baseline means, to present a relative change. All standard errors are clustered at the original facility level, and 95% pointwise confidence intervals are reported.

A Additional Details

A.1 Approach to Measuring Quality

Nursing home quality of care is an inherently difficult object to measure, and the deficiency citations studied in this paper are only one possible metric. Approaches common to industrial organization, such as the use of revealed preferences in consumer demand to infer quality, are broadly ill-suited to health care markets due to the presence of asymmetric information (Arrow 1963). In nursing home markets, patient preferences are particularly difficult to interpret due to the number of agents involved in the nursing home decision (family members, hospital discharge planners, etc.) as well as selective admissions policies unobservably restricting choice sets (Gandhi 2020). Note that although it is common in the literature to employ staffing ratios (such as the number of registered nurse hours per resident day) as a proxy for facility quality, I do not do so here for data limitations. Prior to the introduction of the Payroll Based Journal data in 2016, staffing ratios were measured only once per year and known to be systematically over-stated by facilities (Geng, Stevenson, and Grabowski 2019). Closing facilities, facing financial distress, may have faced differential incentives to over-state their staffing ratios. Accordingly, I instead focus on the more reliable quality of care violations as my primary measure of quality, which I supplement with a standard risk-adjusted survival measure, described in Appendix C.

A.2 Identifying Exits

A common issue in the literature on provider exits is identifying whether a specific facility that exits the data actually shut down, or merely changed the provider identifier due to a merger, acquisition, or new certification (Carroll 2019; Joynt et al. 2015). Previous approaches in the literature on hospital closures have conducted manual searches to identify 'true' exits. Unfortunately, this approach is less feasible in the nursing home setting, as (1) there are about three times as many nursing homes as hospitals, (2) changes in nursing home ownership/name are much more frequent making manual searches more challenging, and (3) exits occur at an order of magnitude greater rate.

To identify nursing home exits, I construct a candidate list of exits by linking the termination dates in the Provider of Service files with the last year a facility is observed in the LTCFocus panel, and by restricting to facilities whose final observed year is within one year of its termination date. For these candidate closures, I then apply the Uber H3 hexagonal spatial index to assign each facility to a narrow tile of approximately 0.1 square kilometers.[19] A closure is 'confirmed' if there is no new facility operating in the tile in the subsequent year. This procedure leaves me with a final sample of 1,104 nursing home exits occurring over the period 2001-2014.

Of course, this procedure may be imperfect. For instance, any transcription errors in the address will result in inaccurate geocoding, which may erroneously lead to a facility being labeled an exit when it did not, though spot-checks and congruence with state-level reports suggests that this concern is minimal. Nonetheless, to the extent that my procedure identifies false closures, the estimated mortality effects will be attenuated towards zero. Moreover, this novel approach to identifying provider exits can be extended to other settings where similar issues arise, such as the literature on hospital closures.

19. I find very similar results when I expand the tile size to 1 square kilometer. Further details available at https://eng.uber.com/h3/.

A.3 Minimum Dataset 2.0 and 3.0 Transition

My analysis spans the transition from the Minimum Dataset 2.0 (MDS 2.0) to the Minimum Dataset 3.0 (MDS 3.0) in October 2010. This transition involved a substantial revision of the MDS data, including changes to which variables are assessed, and largely improved the veracity of the data. Many variables were added to the MDS 3.0 which would be worthy of independent study. For instance, 'patient-focused' variables such as reports of mental health became a primary focus. However, because these variables did not exist in the MDS 2.0, I am unable to examine them for the vast majority of my sample, which spans nursing home exits from 2001-2014.

Fortunately, the only MDS variable that is crucial for my analysis is the facility identifier (the CMS Certification Number), which is consistently defined across the transition. This allows me to identify which residents receive assessments in which facilities in each quarter, allowing me to seamlessly track patients as they move across facilities over time. My main outcome variables — mortality and hospitalization — are measured using Medicare enrollment and claims data, which are consistently defined.

Note that my results do include other measures derived from the MDS. The patient covariates used in my primary results – the variables contained in X_i in equation (1) – includes only variables that are common to both the MDS 2.0 and MDS 3.0. Specifically, this includes the set of diagnosis codes that are common to both datasets, as well as indicators for whether the patient required help with any of the activities of daily living. To address the concern that coding practices for these variables may have changed over time, I engage in several robustness exercises. First, I examine the sensitivity of my results to excluding these variables entirely (Appendix Figure D.6). Second, I examine the sensitivity of my results to an alternative set of risk-adjustors that are derived from Medicare claims, and hence not subject to this transition (Appendix Figure D.7). Reassuringly, both exercises yield nearly identical results to my primary analysis.

A.4 Further Details on Matching Procedure

Matching is done using observed facility characteristics from the year prior to closure. Prospective (control) matches are evaluated by their distance from each treated facility. All matching variables come from the LTCFocus annual panel of nursing homes. Only freestanding (i.e., non-hospital based) nursing homes are considered.

Prospective matches are required to match exactly on the following set of discrete variables: the presence of a specialty Alzheimer's unit, facility ownership (including indicators for both for-profit status as well as chain-ownership), whether the facility is designed as 'concentrated' or 'competitive' based on its Herfindahl-Hirschman Index (HHI), and finally the county in which the facility is located is assigned one of 6 classifications ranging from large central metropolitan area to noncore, which come from the 2013 National Center for Health Statistics Urban-Rural Classification Scheme for Counties.

The Mahalanobis distance is calculated between each prospective match and treated facility using following continuous variables: the shares of the facilty's residents covered by Medicaid and Medicare, respectively, the number of registered nurse/licensed practical nurse/certified nursing aide hours per resident day, the occupancy rate, and an index for patient acuity. Up to 4 matches are considered for each treated facility. Facilities with fewer than 3 viable matches are excluded. Matches that are located in the same county as the treated facility are excluded. Matches can also serve as controls for multiple treated facilities. All facilities are identified using their 6-digit CMS certification number (CCN), i.e. variables AA6B in the MDS 2.0, A0100B in the MDS 3.0, and PROV1680 in the LTCFocus data.

Time trends in each of the matching variables for the selected facilities are shown in Appendix Figure D.2. The trends are smooth and show no evidence of sharp changes immediately preceding or following the reference facility closure. Note that these data are measured annually, so to ensure sufficient pre- and post-period data I restrict the sample to only exits occurring between 2004 and 2015.

B Cumulative Mortality Simulation

The primary object of interest in the paper is the effect on cumulative mortality (ΔM_t, described in equation (2)). Following Deryugina and Molitor (2020), I compute ΔM_t indirectly using estimates of the mortality hazards β^{τ}, estimated via equation (1). One natural question is: why not estimate the model using cumulative mortality directly? The answer is that direct estimation of the cumulative effect on mortality is infeasible in the presence of differences in baseline mortality rates, which necessitates a violation of the parallel trends assumption.

Intuitively, because cumulative mortality converges to one for all groups, any differences in baseline mortality *requires* that cumulative mortality between two groups must not move in parallel. Mortality hazards, however, need not converge to one, and so the parallel trends assumption can be satisfied when considering per-period rates.

To illustrate this point, I conduct a simple simulation exercise. In the simulation, there are two groups of individuals: treated and control. Those in the treated group experience a shock to their per-period mortality hazard, while individuals in the control group do not. This shock resembles the pattern estimated in the main text. In the baseline simulation, all individuals face the same baseline 4% mortality rate. In the second simulation, the treated group faces a slightly higher 4.2% mortality rate. The aim is to explore how the two approaches — inferring the cumulative mortality effect indirectly, as I do in the paper vs. calculating the 'empirical' difference in cumulative mortality between treatment and control groups — perform under each of these scenarios. I simulate the mortality of 1 million individuals over 20 periods, with treatment occurring in period 6.

The results are shown in Figure B.1. The value of the shock (the change in per-period mortality hazards, analogous to β) is plotted in each panel. This pattern is chosen to mirror the results in the paper: the treatment group experiences a large short-run increase in mortality risk, followed by a long-run decline.[20] By construction, there is no violation of parallel trends.

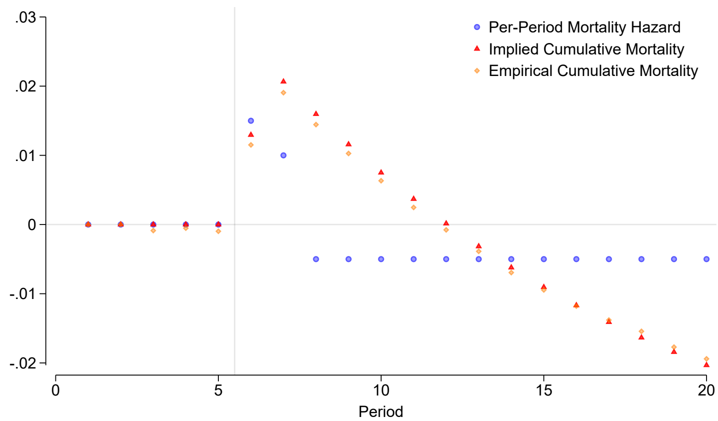
The cumulative mortality effect ΔM_t implied by the values of β is also shown in each panel. Notably, these estimates are the same in both scenarios. Even in the presence of different baseline mortality rates, the method correctly shows no evidence of diverging pre-trends, and correctly calculates the implied effect on cumulative mortality for each period. This follows the standard assumptions of difference-in-differences, that 'balance-in-levels' is not necessary in the dependent variable, only parallel trends.

The 'empirical cumulative mortality' effect, which is the difference in survival curves for the two groups, is also calculated. In the first panel, where there is no difference in baseline mortality rates, the implied and empirical cumulative mortality effects are nearly identical. In contrast, in the second panel, the 'empirical' mortality effect shows immediate divergence between the treatment and control groups, even though there is no parallel trends violation coming from the treatment effect. Instead, this reflects the difference in baseline mortality rates between the treatment and control groups.

This inability of the empirical cumulative mortality effect to differentiate between unequal baseline rates and treatment effects precludes estimation of the effect on cumulative mortality directly, and gives rise to the method employed in the paper. Table 1 in the main text illustrates that there are indeed differences in baseline mortality rates between treatment and control groups, motivating the use of this approach rather than direct estimation of cumulative mortality effects.

20. That is, the hazard effects are briefly large and positive and then small and negative for the remainder of the panel.

(a) Identical Baseline Mortality Rates



(b) Different Baseline Mortality Rates

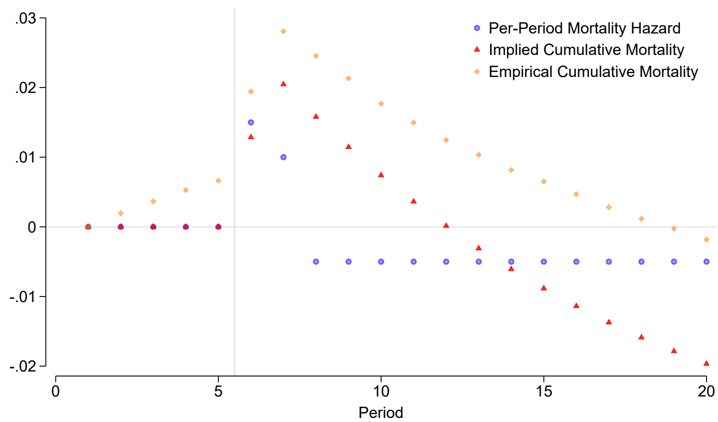


Figure B.1: Simulation Results

Notes: Figures present the results of a simulation exercise to explore the efficacy of inferring the effect on cumulative mortality, comparing treatment and control groups. The Implied Cumulative Mortality series reflects the cumulative mortality effect inferred using the method described in the paper. The Empirical Cumulative Mortality series calculates the effect taking the difference in survival curves between treatment and control groups. Panel (a) assumes that the treatment and control groups have identical baseline mortality rates. Panel (b) assumes that the treatment and control groups have different baseline mortality rates.

C Risk-Adjusted Survival Quality Measure

Models of risk-adjusted survival/mortality are common in the literature on health care quality estimation (e.g., Doyle Jr et al. 2015; Chandra et al. 2016). Following this literature, I construct a comparable measure of nursing home quality based on the risk-adjusted 90-day survival rates for all new patients (i.e., including both short-stay and eventual long-stay residents). While risk-adjusted survival from admission may have limited applicability to my sample of long-stay nursing home residents (who by definition have survived beyond 90 days after admission), it is a useful exercise to understand how the landscape of quality changes for short-stay residents after a facility closure.

To calculate risk-adjusted survival rates, I estimate a fixed effects regression of the form:

$$Y_i = \theta_{j(i),t(i)} + \alpha X_i + \eta_i$$

where i and j index admissions and facilities, respectively, t indexes a two-year bin (e.g., 2000 and 2001), Y_i is an indicator for whether the patient survives 90 days past admission and X_i is a vector of patient characteristics. The parameters of interest are the facility fixed effects $\theta_{j(i),t(i)}$, which can vary at the two-year bin-level. These terms capture the facility-specific component of the 90-day survival rate. Allowing the facility-specific effects to evolve over time is important, as one of the goals of this analysis is to measure how the distribution of quality in a market changes following a closure.

As in my main analyses, this sample is restricted to patients who are enrolled in the Medicare program, for whom I observe mortality in any setting (i.e., including at home or in the hospital). The vector of risk-adjustors X_i includes demographic information such as patient age, sex, and race as well as indicators for the presence of 26 comorbidities. My sample includes 19,070,127 nursing home admissions over the period 2000-2017. This sample excludes any admissions that occur within 90 days of a facility exit.

The results suggest that there is considerable dispersion in nursing home quality, consistent with existing estimates (Einav, Finkelstein, and Mahoney 2022; Cheng 2023). I find a one standard deviation increase in quality corresponds to a 5.38 percentage point increase in survival. The full distribution of resulting quality estimates is presented in Appendix Figure C.1.

Using this alternative measure, I examine the distribution of quality for several groups of facilities (Appendix Table C.1). Consistent with my primary results, exiting facilities appear to be low quality. Relative to other facilities in the market, exiting facilities have slightly lower mean quality (82.4% mean risk-adjusted survival, compared to 83.6% for the average facility in a market with an exit in that year-bin.) Notably, these means mask much of the differences in quality, which is in the far left-tail. The 5th percentile for closing facilities is only 70.6%, considerably lower than the corresponding percentile for other facilities in the market (74.5%).

Turning to the quality of 'absorbing' facilities to which displaced residents transfer, I again find results consistent with my primary analyses. Absorbing facilities appear to have much higher quality than exiting facilities, both at the mean and particularly in the left tail. The 5th percentile of quality in this group is 74.7%. Overall, absorbing facilities appear similar to the broader set of non-closing facilities, suggesting that patients are not reallocating to facilities that are particularly high- or low-quality. These results mirror my analysis of the distribution of quality-of-care deficiency citations: while there is much overlap in the distributions of quality, closing facilities are over-represented in the low-quality tail (Appendix Figure D.16).

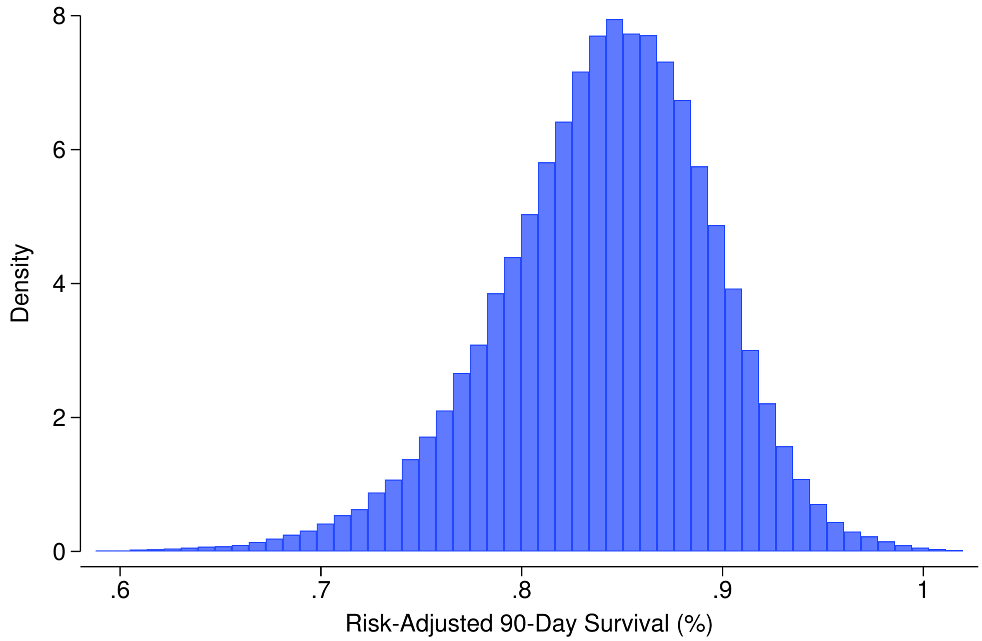


Figure C.1: Distribution of Risk-Adjusted 90-Day Survival Estimates

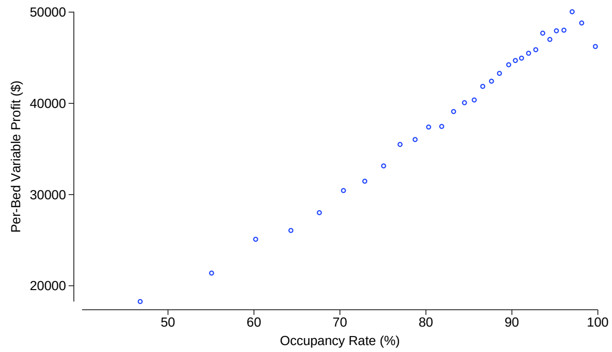
Notes: Figure presents the distribution of risk-adjusted 90-day survival estimates. Each observation is a facility-two year pair. Estimates are computed using all new nursing home admissions from 2000-2017 (excluding admissions within 90 days of a facility exit or the end of the sample). Estimates are trimmed at the 0.5th and 99.5th percentiles.

	Mean (1)	P5 (2)	P25 (3)	P50 (4)	P75 (5)	P95 (6)
Closing Facilities	82.42	70.63	78.46	82.76	87.12	92.24
Absorbing Facilities	83.53	74.69	80.35	83.82	86.98	91.27
Other Facilities in Market	83.57	74.45	79.93	83.88	87.22	92.42
Comparison Facilities	83.20	73.63	79.64	83.55	87.00	91.71

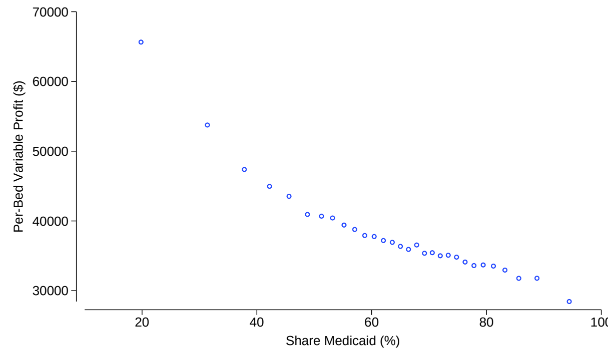
Table C.1: Distribution of Quality by Facility Status

Notes: Table presents the distributions of 90-day risk adjusted survival by facility status. Estimates correspond to the mean, 5th, 25th, 50th, 75th, and 95th percentiles. Risk-adjusted survival is computed using all nursing home admissions from 2000-2017.

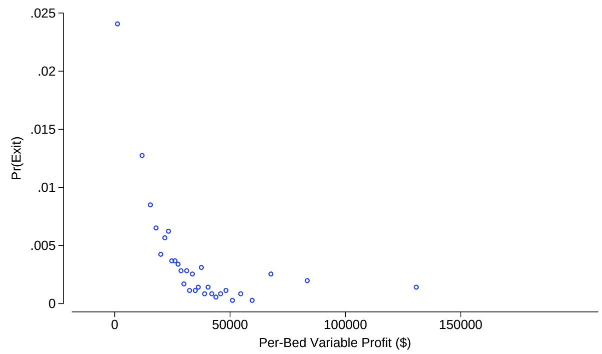
D Additional Tables and Figures



(a) Variable Profits by Occupancy Rate



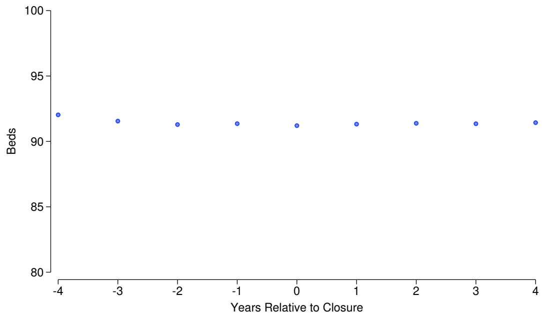
(b) Variable Profits by Medicaid Share



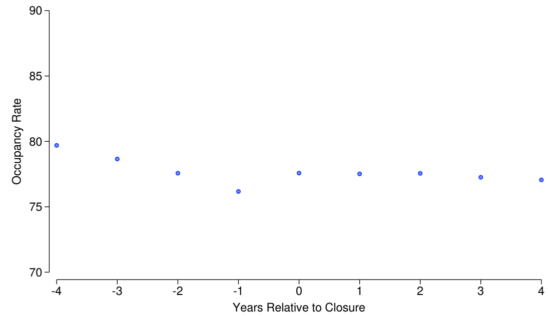
(c) Exit Rate by Variable Profit

Figure D.1: Determinants of Nursing Facility Exits
Notes: Figures present binned scatterplots of facility-year variable profits, exit probabilities, occupancy rates, and shares of patients whose stays are funded by Medicaid. Data on occupancy and Medicaid shares come from the LTCFocus.org database, while data on profits come from the Medicare Cost Reports, and span the period 2011-2019. Exits are defined in Section A.2.

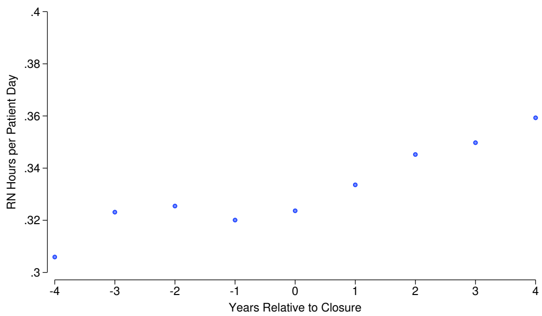
(a) Total Beds



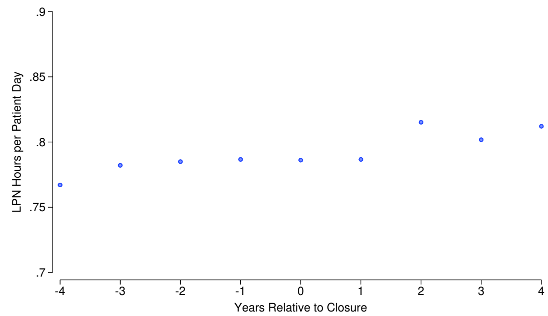
(b) Occupancy Percentage



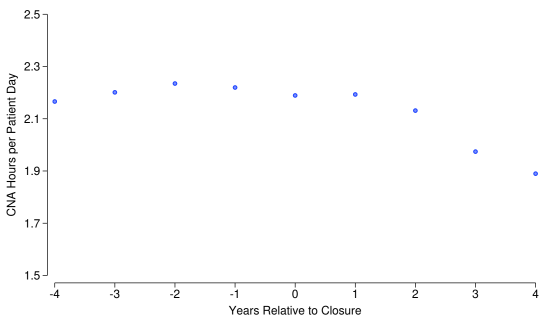
(c) RN Hours per Patient Day



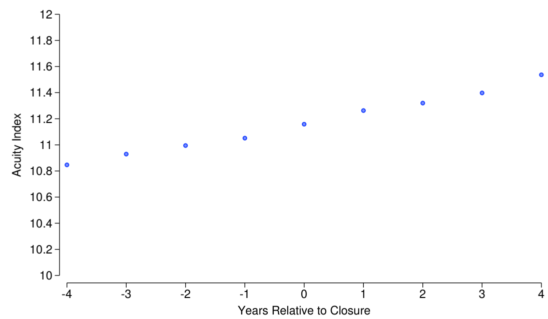
(d) LPN Hours per Patient Day



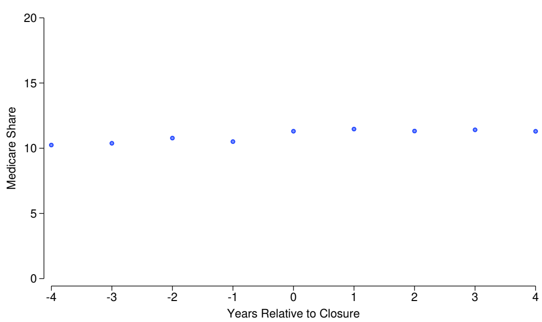
(e) CNA Hours per Patient Day



(f) Acuity Index



(g) Medicare Share



(h) Medicaid Share

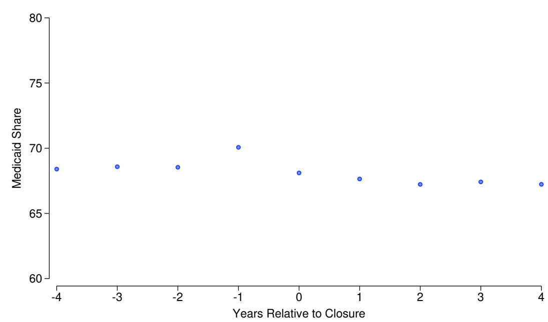
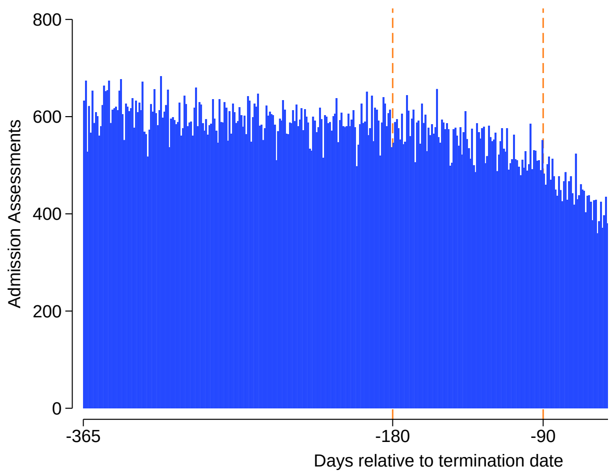
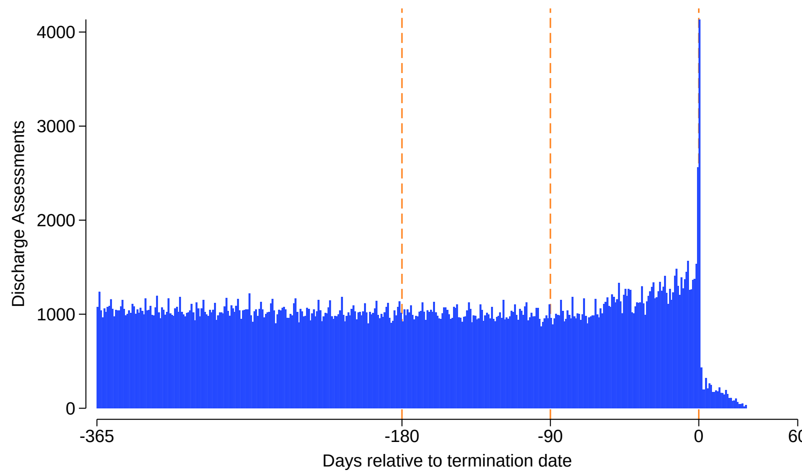


Figure D.2: Trends for Matching Variables

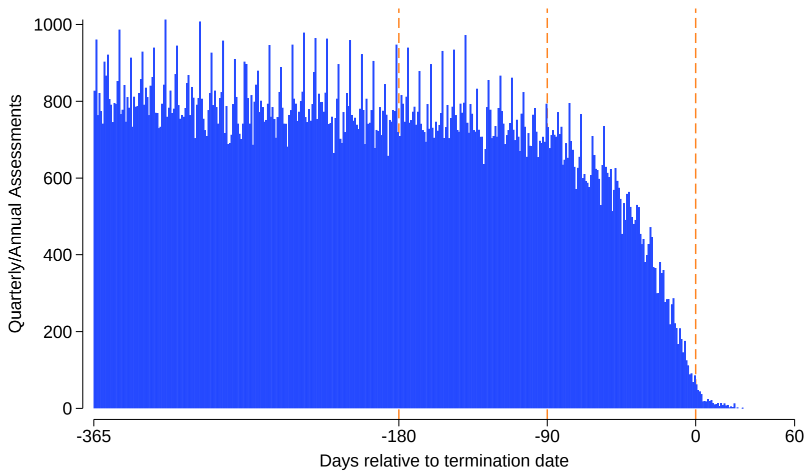
Notes: Figures present time trends in the continuous variables used in the matching procedure for the selected controls, relative to their reference facility's closure date. Data are drawn from the LTCFocus.org database.



(a) Admission Assessments



(b) Discharge Assessments



(c) Quarterly/Annual Assessments

Figure D.3: Counts of Assessments Relative to Exit Date

Notes: Figures present total daily counts of assessments across exiting facilities, by the date relative to its termination from Medicare and Medicaid. Figure (a) presents the counts of assessments corresponding to new admissions, which appears approximately stable until 90 days before the exit date, at which point they begin to taper. Figure (b) presents counts of discharge assessments, which also appear stable until 90 days before the exit date, at which point they rise sharply, with the largest spike occurring exactly on the date of exit. Figure (c) presents the counts of regular (quarterly or annual) assessments, which appear to follow a similar pattern as the admission assessments.

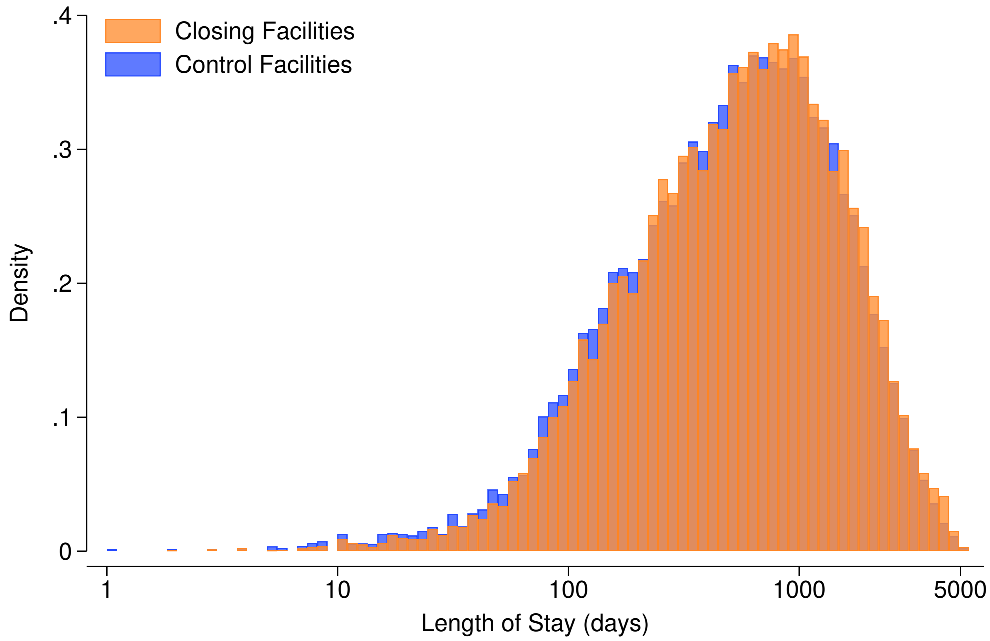


Figure D.4: Distribution of Length of Stay Prior to Closure

Notes: Figure presents the distribution of patient length of stay prior to facility closure. Histogram presented separately for patients in closing facilities and their matched controls.

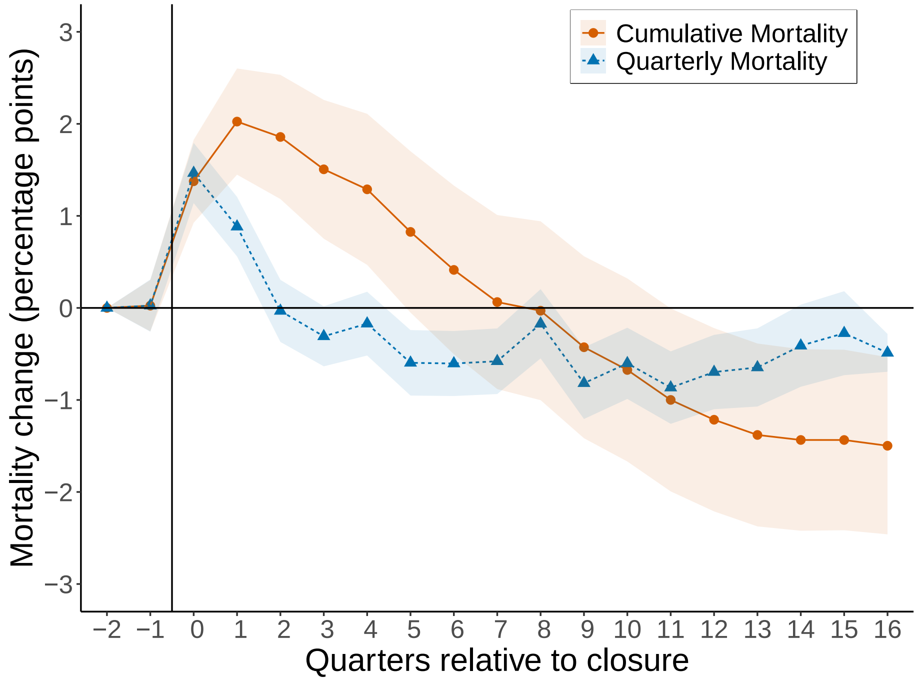


Figure D.5: Mortality Estimates with Extended Follow-Up

Notes: Figure presents estimates from a modified version of equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort, that extends the follow-up period from the baseline 12-quarter to a longer 16-quarter window. The sample is restricted to facilities that closed prior to 2014 to ensure a balanced follow-up period.

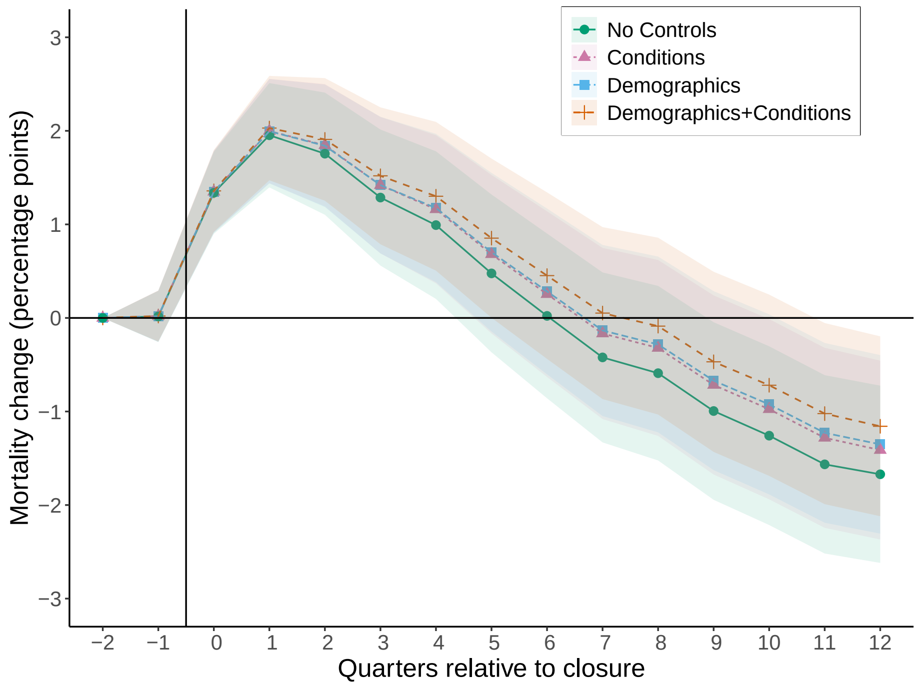


Figure D.6: Test of Coefficient Stability

Notes: Figure presents several estimates of the cumulative mortality effect (ΔM_t) for the baseline resident cohort, allowing for differing levels of controls X_i.

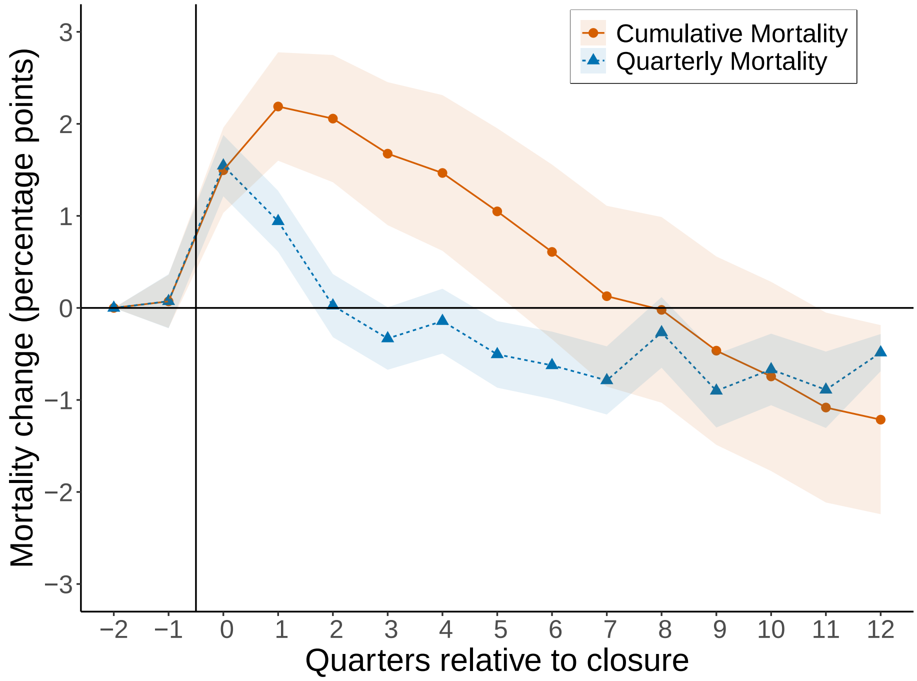
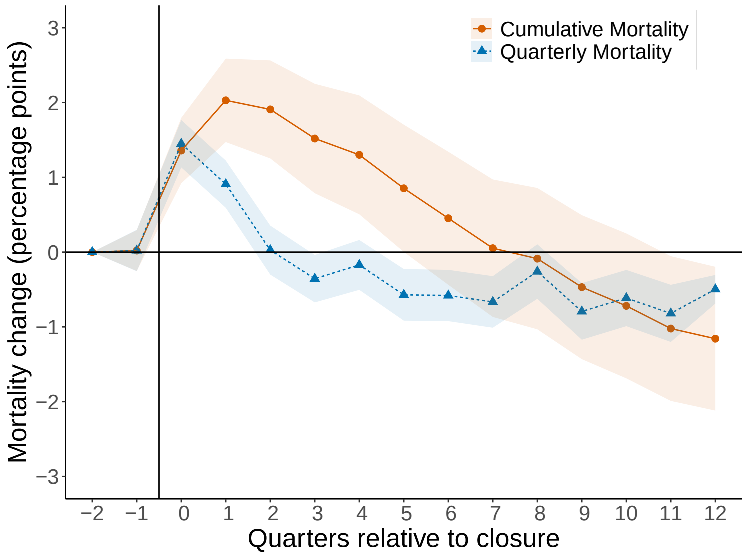


Figure D.7: Mortality Effect with Claims-Derived Controls

Notes: Figure presents estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort, which in addition to the usual demographic variables, also includes a vector of 24 chronic condition indicators present in the Beneficiary Summary File. Because these codes are not well defined for Medicare Advantage patients, I restrict the sample to only fee-for-service Medicare enrollees.

(a) 2-Quarter Cohort



(b) 4-Quarter Cohort

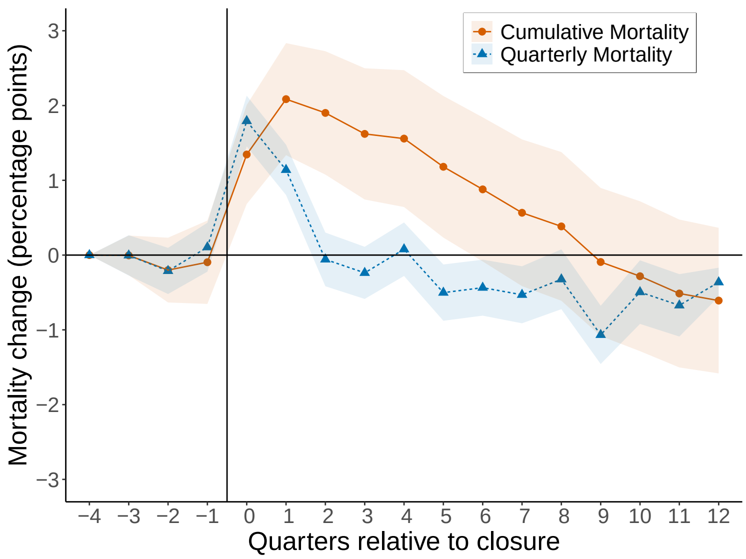
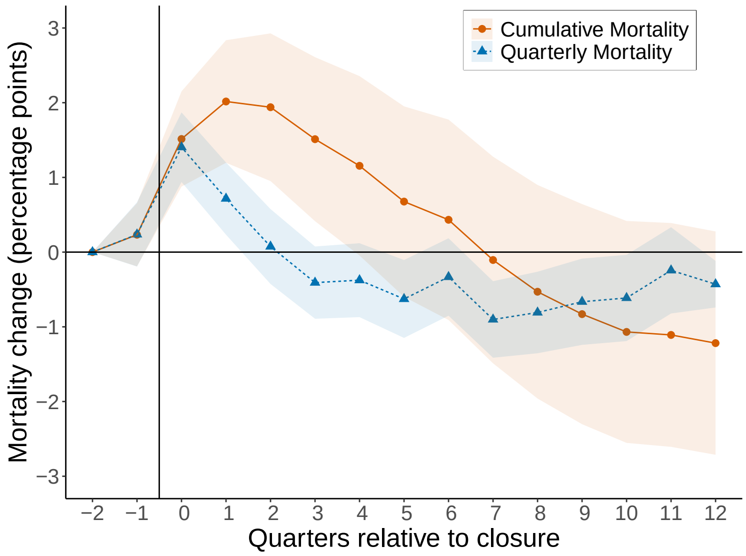


Figure D.8: Estimates Excluding Involuntary Closures

Notes: Figure presents estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) excluding the 6.9% of facility closures that are associated with an involuntary termination from the Medicare/Medicaid programs.

(a) 2-Quarter Cohort



(b) 4-Quarter Cohort

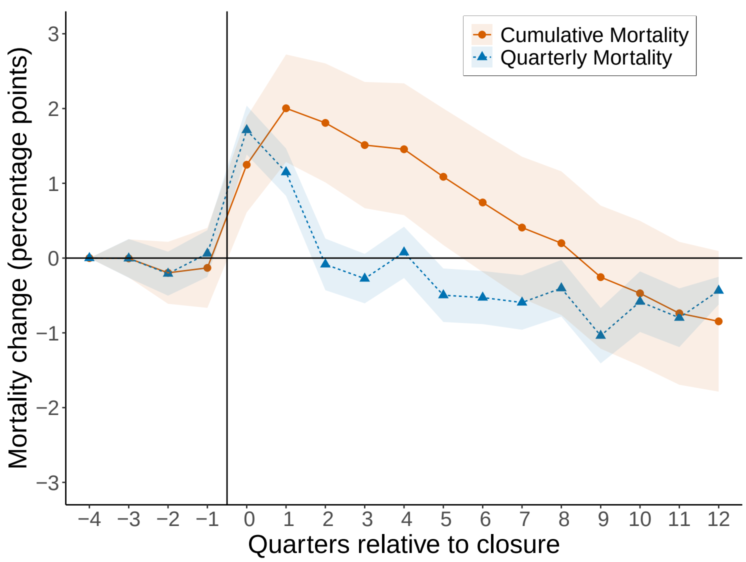
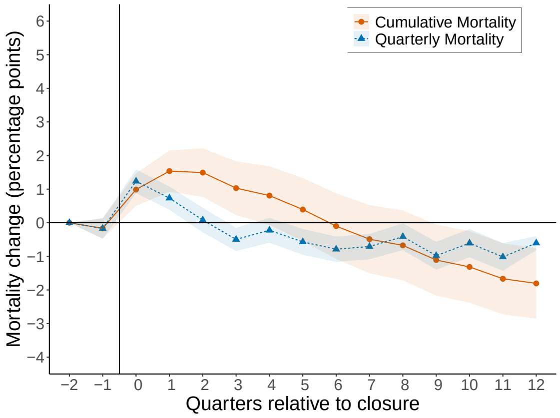


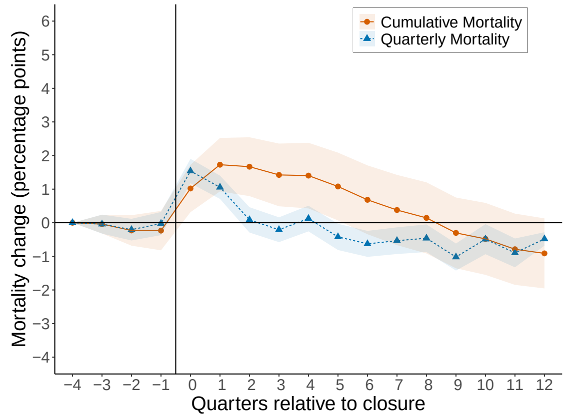
Figure D.9: Estimates from Alternative Matching

Notes: Figure presents estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for an alternative cohort of residents that come from incorporating quality-of-care deficiencies in the matching procedure. Sample is limited to 2007-2014 due to data restrictions.

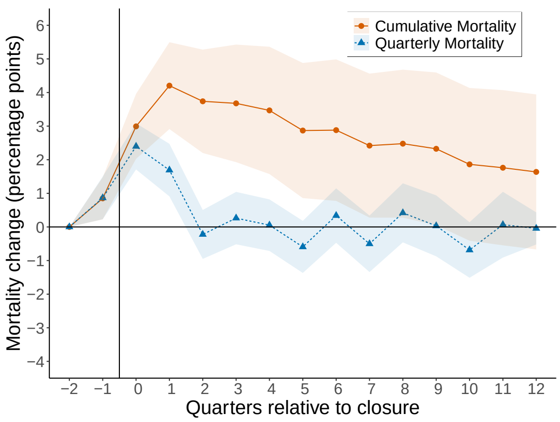
(a) 2-Quarter Cohort: Competitive Counties



(b) 4-Quarter Cohort: Competitive Counties



(c) 2-Quarter Cohort: Non-Competitive Counties



(d) 4-Quarter Cohort: Non-Competitive Counties

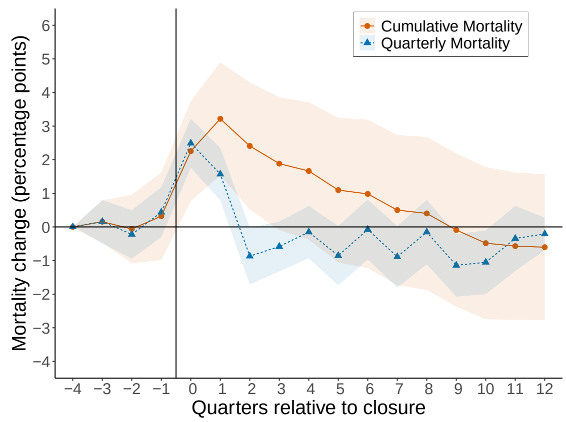


Figure D.10: Mortality Change by County-Level Market Concentration

Notes: Figures present estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort by the level of pre-closure competition, using a county-level HHI measure. Given the larger market definition, I set the threshold for concentrated markets to those with HHIs above 2,500, which produces approximately the same share of facilities defined as concentrated as in the main definition.

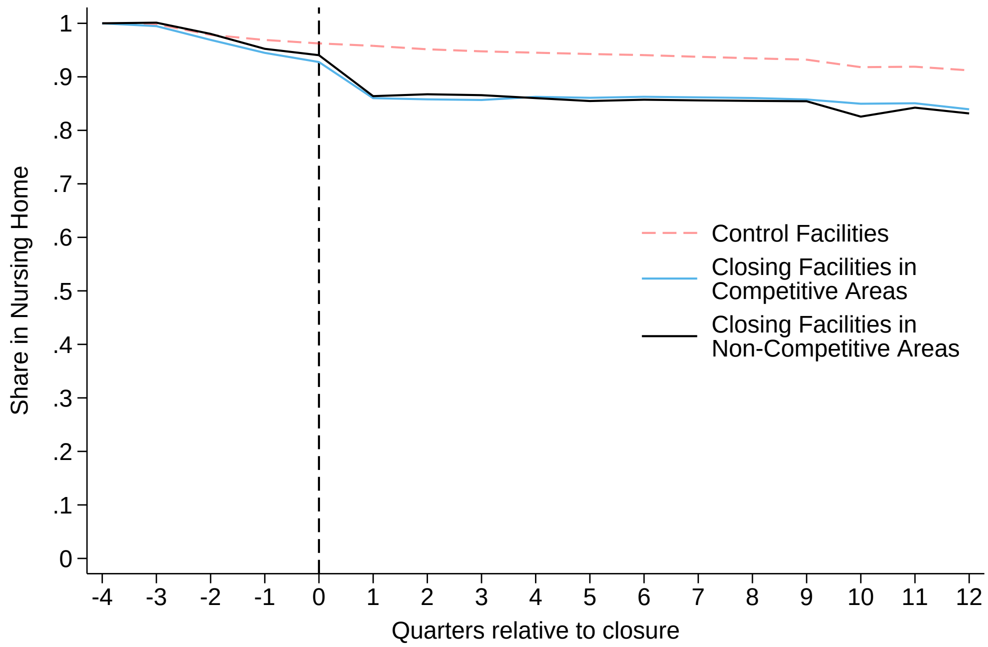
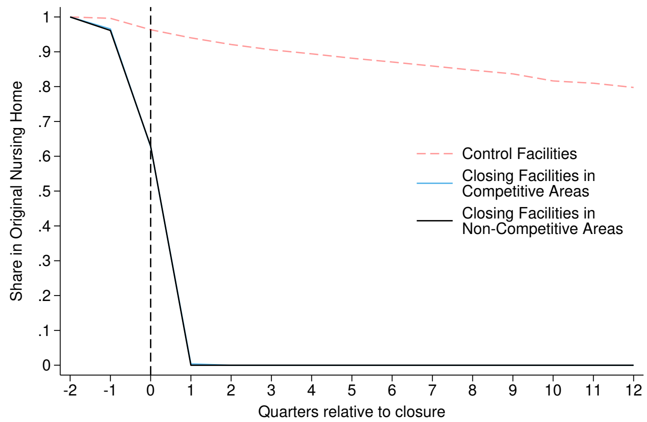


Figure D.11: Share of Surviving Cohort Still Present in a Nursing Home: 4-Quarter Cohort

Notes: Figures present the empirical share of residents who are still in a nursing home for the 4-quarter lookback cohort.

(a) 2-Quarter Cohort



(b) 4-Quarter Cohort

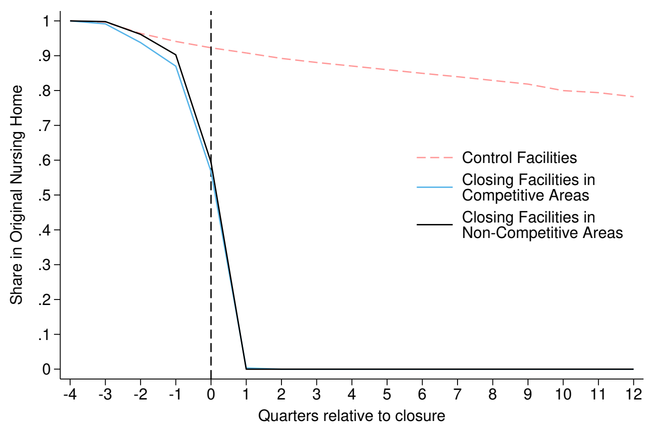


Figure D.12: Share of Surviving Cohort Present in Original Nursing Home

Notes: Figures present the empirical share of residents who are still in their original nursing home. Top panel presents estimates for the 2-quarter lookback cohort. Bottom panel presents estimates for the 4-quarter lookback cohort.

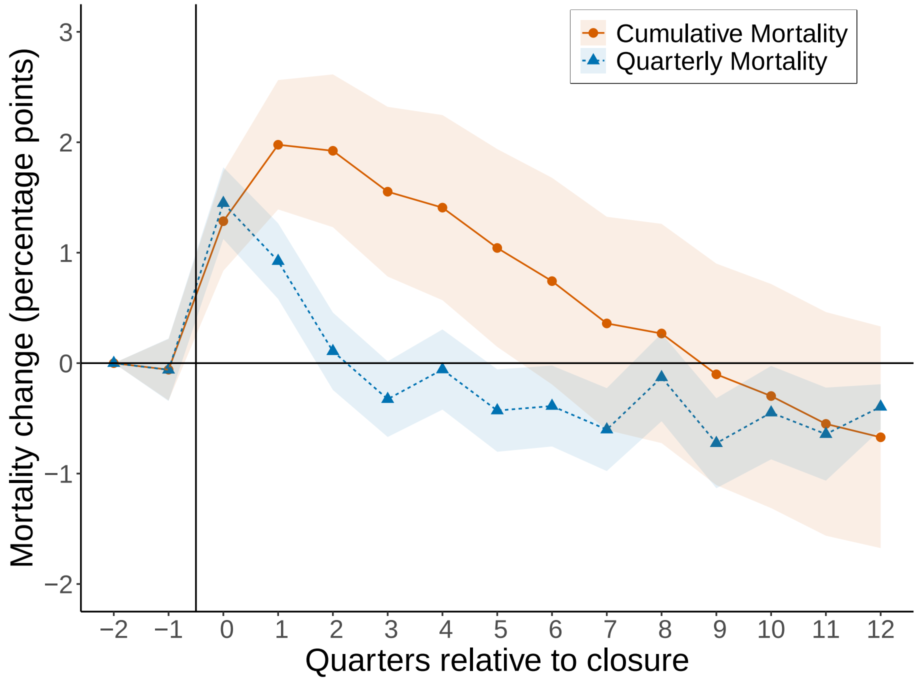


Figure D.13: Mortality Rate Relative to Closure

Notes: Figure presents estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort, restricted to patients who are continuously present in any nursing home.

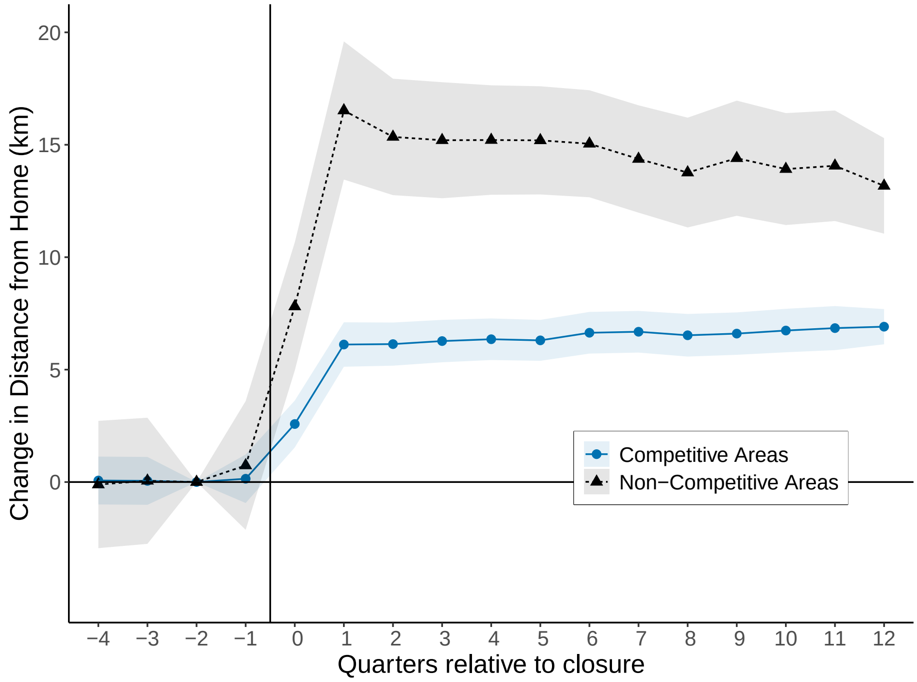
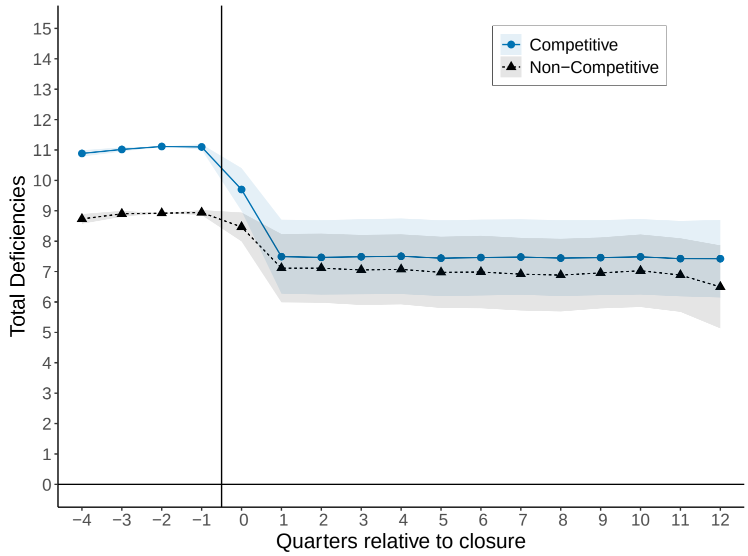


Figure D.14: Distance from home zip code

Notes: Figure shows how far patients are displaced following their nursing home closure, presenting β^{τ} estimates of equation (1) with the distance from the resident's home zip code to their current nursing home in each quarter as the dependent variable. Distance is determined using the resident's last 5-digit zip code (from the Medicare enrollment records) prior to their initial nursing home stay. Heterogeneous effects are estimated jointly, interacting the concentration measure with the relative time indicators. Patients who do not transfer to a new nursing home are excluded.

(a) Total Deficiency Citations



(b) Deficiencies for Actual Harm/Jeopardy

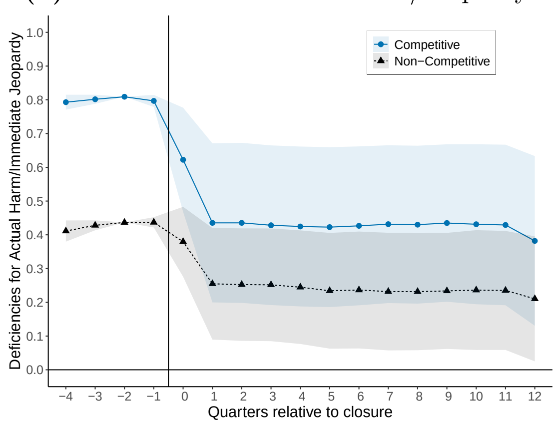


Figure D.15: Alternative Deficiency Citation Measures

Notes: Figure presents how patients reallocate following their displacement from a closing nursing home. The top panel reports the total deficiency citations of the resident's current facility. The bottom panel presents results restricting to only deficiency citations for actual harm or immediate jeopardy, the most severe categories. These figures are analogues to Figure 7c in the main text, which considers only quality of care violations. Patients who do not transfer to a new nursing home are excluded.

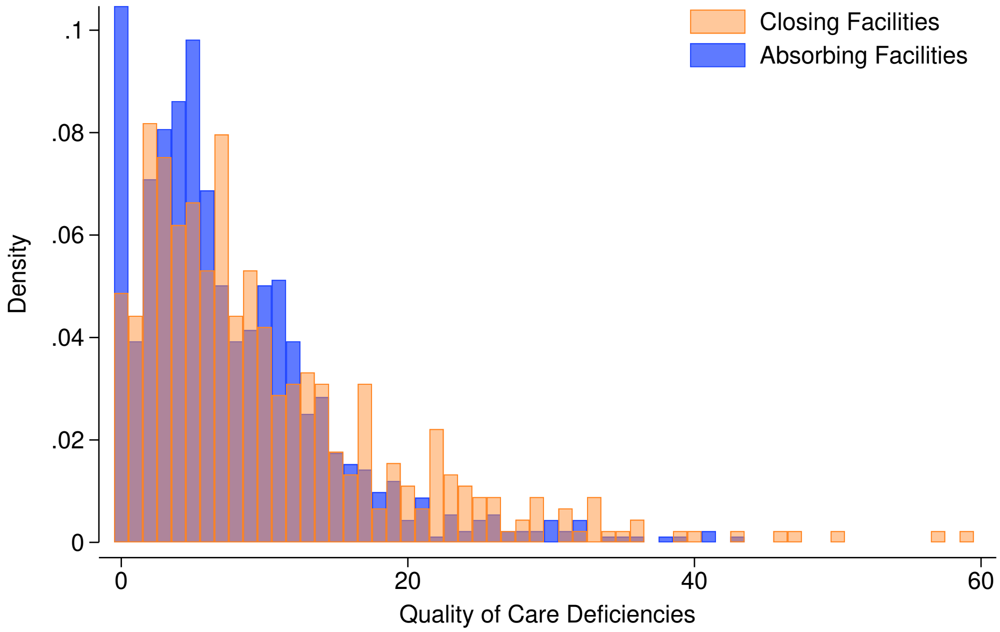


Figure D.16: Distribution of Quality of Care Deficiencies

Notes: Figure presents the distribution of quality-of-care deficiencies for each closing facility, as well as the set of 'absorbing' facilities, defined as the first facility a treated patient moves to following closure.

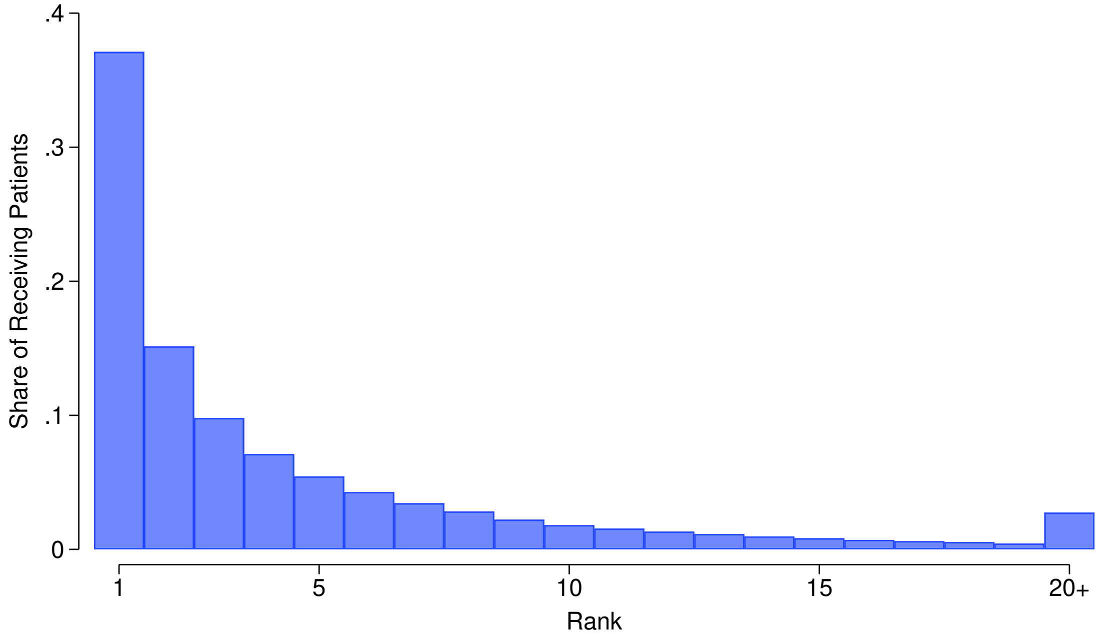


Figure D.17: Absorbing Facilities

Notes: Figure presents the distribution of absorbing facilities for residents displaced by nursing home closures. The figure shows the share of residents from the closing facility that move to the facility that receives the kth most residents. The figure shows that 37.1% of residents move to the most common receiving facility, and 52.2% move to one of the top two facilities. Figure is top-coded at the 20th ranked facility.

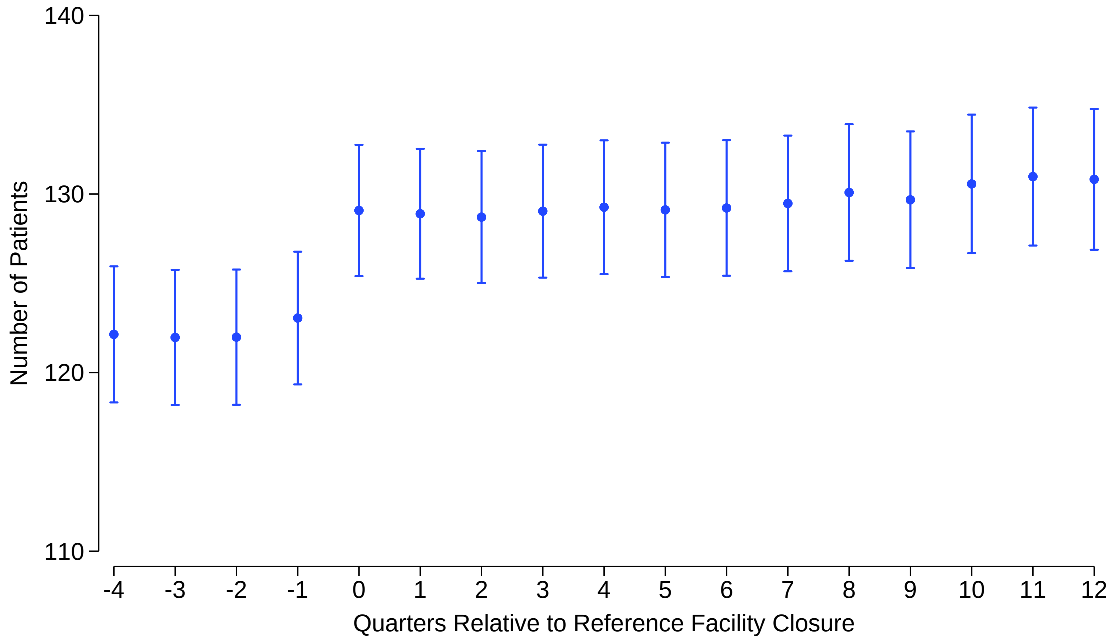


Figure D.18: Number of Patients in Absorbing Facilities

Notes: Figure presents the number of unique quarterly patients assessed in the absorbing facilities by quarter relative to the reference facility's closure date. Figure is restricted to the facilities that receive either the highest or second highest number of displaced patients.

Category	Short-Stay (1)	Long-Stay (2)
Total	13,280	15,641
Hospital Inpatient	4,140	4,852
Hospital Outpatient	1,846	1,770
Physician Office	1,736	1,661
Prescription Drug	1,432	1,410
Home Health	861	1,485
Other Inpatient	667	1,075
Hospice	183	305
Other	2,414	3,084

Table D.1: Average Annual Medicare Spending for Nursing Home Residents Prior to Admission

Notes: Table presents average annual Medicare spending by short-stay and long-stay patient status. Estimates calculated using the year prior to nursing home admission to avoid any differences in costs associated with nursing home use.

Data Source	Years	Relevant Data
MDS	2000-2017	Demographics, health measures, nursing home stays
BSF	2000-2017	Mortality dates, home zip codes, health measures, Medicaid eligibility
MedPAR	2000-2017	Hospital admission, Medicare coverage
LTCFocus	2000-2017	Nursing home characteristics
Deficiency Surveys	2006-2017	Deficiency citations
Medicare Cost Reports	2011-2017	Nursing home financials

Table D.2: Data Sources

Notes: Table lists each data source, the years spanned and the relevant data contained therein.

	Closed Firms (1)	Matched Firms (2)	All Non-Closed Firms (3)
Facility Characteristics			
Total Beds	84.6 (57.5)	94.6 (48.3)	110.5 (61.5)
Alzheimer's Unit, %	9.1 (28.7)	9.4 (29.2)	18.9 (39.1)
For-Profit, %	74.4 (43.7)	72.8 (44.5)	71.9 (45.0)
Concentrated, %	31.0 (46.3)	29.6 (45.7)	30.6 (46.1)
County Population, %			
Large Central Metro	24.5 (43.0)	25.6 (43.6)	21.3 (40.9)
Suburban	14.8 (35.5)	15.0 (35.7)	19.9 (39.9)
Small/Medium Metro	28.6 (45.2)	29.2 (45.5)	30.3 (46.0)
Rural	32.2 (46.7)	30.2 (45.9)	28.4 (45.1)
Patient Characteristics, %			
Occupancy	70.4 (19.1)	76.9 (16.1)	84.8 (14.3)
Medicaid	74.0 (20.1)	71.0 (18.7)	63.0 (22.0)
Private-Pay	18.2 (16.8)	19.0 (14.9)	24.7 (19.0)
Profit Margin, %	-8.8 (12.4)	-0.7 (9.9)	1.8 (9.2)
N	1,104	3,812	197,802

Table D.3: Facility Summary Statistics

Notes: Table presents summary statistics on the exiting facilities, their matched controls, and the universe of non-exiting facilities collected from LTCFocus.org and the Medicare cost reports. Standard deviations are reported in parentheses. Observations in columns (1) and (2) are drawn from the year prior to closure. Column (3) includes all observations for each non-closing facility. Because the distribution of exit years is not uniform, the observations in (3) are weighted to reflect the distribution of exit years, in order to facilitate comparison.