Reallocation and the (In)efficiency of Exit in the U.S. Nursing Home Industry

Andrew Olenski[*]

Department of Economics
Lehigh University

December 4, 2023

Abstract

This paper examines the impacts of healthcare provider exits on patient outcomes and subsequent reallocation. Leveraging data on the universe of nursing home patients, I estimate the mortality effects of 1,109 nursing home closures on incumbent residents via a difference-in-differences approach. I find that displaced residents face a short-run 15.7% relative increase in their mortality risk. This increase is offset by long-run survival improvements, so the cumulative effect is a net decline in mortality risk. The vast majority of patients transfer to new, higher-quality firms. There is significant heterogeneity by market concentration: only patients in competitive markets benefit from reallocation.

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 implications of these closures for incumbent residents who are displaced, nor about how they reallocate to new providers.

Nursing home closures may entail countervailing forces for incumbent residents. On one hand, patients who are displaced may fare worse due to potential disruptions in care continuity, declines in quality in the final weeks of a facility's life, and forced changes in environment for an already vulnerable population. Conversely, 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. Understanding these effects is therefore crucial to assessing the desirability of policies aimed at sustaining financially vulnerable providers.

In this paper, I study the mortality effects of 1,109 nursing home closures for incumbent residents. To explore the trade-offs between the immediate disruptive costs and the long-term benefits of reallocation, 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 nursing home residents. I find that nursing home residents experience a 1.14 percentage point increase in their short-run risk of mortality after the facility closes, representing a 15.7% increase over the baseline rate. Following this initial spike, however, mortality risk among surviving patients falls significantly, such that cumulative long-term mortality is 1.23 percentage points *lower* than if the facility had not exited, even inclusive of the initial increase. These gains primarily accrue to younger patients and those without Alzheimer's disease or a related dementia. Older and sicker residents experience only the sharp short-run increases in mortality, with no survival gains. These results are not driven by short-term mortality displacement, also known as 'harvesting.' Rather, I explain these effects by using state-issued deficiency citations to show that exiting facilities are of particularly low quality, and that surviving patients reallocate to higher-quality firms.

Yet this reallocative force does not operate everywhere. I 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 survival gains from patient reallocation 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 none of the 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 results illustrate a phenomenon which is unlikely to be unique to the nursing home

---

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).

industry: there are often gains from reallocating economic activity to high-productivity (or high-quality) firms, but such reallocation may be costly in the short-run. Moreover, the geographic heterogeneity suggest that broad policy efforts to avert nursing home closures may be misguided, and that more targeted subsidies to access to care in vulnerable areas may be more effective.

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. 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.

I also contribute to the small but growing body of research on the economics of the nursing home industry (Gandhi 2020; Lin 2015; Ching, Hayashi, and Wang 2015; Hackmann, Pohl, and Ziebarth 2021; Grabowski, Gruber, and Angelelli 2008; Gupta et al. 2021; Gandhi, Song, and Upadrashta 2020; Hackmann 2019), with a primary focus on the consequences of provider exits. 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

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

The nursing home industry is a substantial component of the economy. Comprising approximately 1% of U.S. GDP and housing 2.4% 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 7% of all government health care spending.

Despite aging demographics, the nursing home industry has been marked by an aggregate decline over the past few decades. From 2000 to 2019, the total number of facilities shrank 13.6% from 16,964 to 14,650 (Appendix Figure B.1), even as the senior population grew by more than 50%. This contraction is characterized by considerable geographic heterogeneity: rural areas have been particularly hard hit by diminishing access to nursing home care. Appendix Figure B.2 documents that rural counties have experienced the steepest declines in capacity over this period, with the largest declines occurring in Midwestern states. This wave of rural nursing home exits has generated considerable media attention, documenting stories of residents who are displaced by significant distances, emphasizing the burden such closures place on their families (Healy 2019; Saslow 2019).

Industry analysts 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. Although research on the topic is more scant, the finding have consistently corroborated industry claims. Nursing homes with lower Medicaid rates and higher shares of Medicaid residents report lower profits and are routinely found to be more likely to exit (Castle et al. 2009; Zinn et al. 2009).

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 regulated than nursing homes, and accept only private-pay residents, with few exceptions.

2.2 Public Concerns over Quality of Care

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 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. 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). I discuss trade-offs of using alternative measures of quality in Appendix Section A.1.

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 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. I measure short-stay acute care hospitalizations for the 88.3% of my sample who are enrolled in Fee-for-Service (Traditional) Medicare using the Medicare Provider and Analysis Review (MedPAR) files.

In addition, I also combine a variety of 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). Finally, remaining facility characteristics are collected from the OS-CAR/CASPER data, accessed through LTCFocus.org.[2] (Appendix Table B.1 contains information on all data sources used.)

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.

---

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

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. 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. Appendix Table B.2 provides summary statistics on both the exiting facilities and the matched sample from the year prior to exit, in addition 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 much closer in size (84.8 beds compared to 91.9), have comparable shares of private-pay patients (approximately 18%), and are similarly distributed across rural and urban areas.

This approach to estimating the effect of nursing home closures 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' shutdown decisions – which may be endogenous to demand – are orthogonal to any idiosyncratic health shocks to *incumbent* residents in the period around the closure. Mortality rates between residents of the treatment and control facilities trend in parallel in the year prior to closure, supporting this assumption.

Identifying the mortality effects of a nursing home closure also requires defining the set of patients who are impacted by the exit. 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. This sample may further be polluted by 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 attrition bias, 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 taper (Appendix Figure B.3). These patterns motivate a baseline cohort of treated residents as those who are in the facility two quarters prior to the exit date.[3] 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 will be attenuated

---

3. 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).

for this cohort (who 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.

This procedure results in 43,248 treated patients and 204,010 control patients during the window 2001-2014.[4] Table B.3 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). 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).

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. 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.

My main specification is as follows:

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

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. I 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 match-cohort-by-quarter fixed effect, where cohorts are defined as the exiting facility and its matched controls. X_{it} is a vector of patient-level covariates, including demographics and chronic conditions present at baseline. The focal parameters are β^τ, which capture how the change in the treated residents' mortality between the reference quarter and quarter τ diverges from the change in the control residents' mortality over the same period. Standard errors are clustered at the facility-level.

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

---

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

Molitor (2020) and compute the cumulative mortality effect for each relative quarter t:[5]

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

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.[6] I estimate ΔM_t and its analytic standard error using the β^τ estimates from equation (1) and the delta method.

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 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 deficiency citations. 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 88.3% 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.

---

5. Although the cumulative mortality effect is the primary object of interest, it is not feasible to estimate ΔM_t directly. This is because survival rates converge to zero for all cohorts. Hence, any level differences in baseline mortality risk between the treatment and control groups imply that their survival curves would not have moved in parallel in the absence of treatment. However, there is no reason for the quarterly mortality hazards to converge over time, and so I use β^τ to calculate the implied changes in cumulative mortality.

6. For 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 (Deryugina and Molitor 2020).

Additionally, I examine how nursing homes themselves contribute to the mortality effect. Walsh et al. (2012) identify a set of primary diagnoses (such as infection, 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.

4   Results

4.1   Preliminary Evidence

Before turning to the regression estimates, I examine preliminary empirical evidence on the relationship between nursing home exit and resident mortality and subsequent survival. Figure 1a plots the facility-level raw quarterly mortality rate of all long-stay residents present in exiting firms. The quarterly mortality rate remains flat in the period preceding the shutdown date, and then spikes in the quarter of exit.

To explore the long-run effects of exit on resident survival, Figure 1b plots the unadjusted cumulative survival (Kaplan-Meier curves) of all displaced residents who were present in a closing facility two quarters prior to exit, along with those in the matched control facilities. These curves illustrate that the long-run survival rate for the displaced residents lies *above* the survival rate for residents who were not affected by a closure.

4.2   Effects of Nursing Home Exits on Mortality

Overall Mortality — The quarterly (β^τ) and cumulative (ΔM_t) mortality estimates are plotted in Figure 2 and summarized in Appendix Table B.4. Panel 2a presents the main results, for the resident cohort present in relative quarter $\tau = -2$. These results indicate a sharp short-run increase of 1.14 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 15.7% 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 seventh quarter after closure. Cumulative mortality continues to decline, and by the third year after closure settles at 1.23 percentage points *lower* than if resident mortality rates had evolved parallel to the control group.

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. Panel 2b 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. 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 meaningfully across clinically meaningful patient covariates. A large share (56.6%) of long-term residents suffer from Alzheimer's disease or another 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 Panels 2c-2d. Indeed, I find a particularly large initial mortality effect of 1.98 percentage points in this subgroup. Similar heterogeneity exists when subsetting by age at baseline (Panels 2e-2f): patients who are at least 80 years old experience an extremely sharp 2.40 percentage point increase in mortality immediately after closure, whereas younger patients experience only a 0.57 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 specification, shown in Appendix Figure B.4 (which omits the estimates of β^τ for clarity), demonstrates that the role of the covariates is limited. The inclusion of demographic controls very slightly attenuates the estimate 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 88.3% 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, in Appendix Figure B.5. These results suggest that concern over the residual imbalance indicated by Appendix Table B.3 is minimal.

4.3 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 (Appendix Figure B.2), 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[7] of each facility in the year prior to exit. The distribution of resulting HHIs in the analysis sample is presented in Appendix Figure B.6. 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

---

7. 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, Appendix Figure B.8 demonstrates that using a more standard county-level HHI measure generates nearly identical results.

as competitive.

I estimate equation (1) separately by competition group. Figure 3 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 (1.08 percentage points), and by 12 quarters after closure have a cumulative mortality probability that is 1.82 percentage points lower. Conversely, residents of facilities in non-competitive areas experience a very large initial mortality increase in the period immediately following closure (1.36 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 fo 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 Appendix Figure B.7.[8] 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.

4.4 Reallocation Across Facilities

Where do displaced residents go? In Figure 4a, I calculate the quarterly share of the surviving cohort who remain in any nursing home (Appendix Figure B.9 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, 84.6% of surviving residents still appear in another nursing home. 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. The results are plotted in Appendix Figure B.10. I find that the mortality trends look similar in this subgroup of transferred patients, though the effects are somewhat attenuated.

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. Relying on the results of annual deficiency 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. Additionally, I examine changes in the presence of severe deficiencies indicating actual patient harm or immediate jeopardy. 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.

---

8. For clarity, I omit the quarterly mortality estimates β^τ.

These results, documented in Figures 4b and 4c, indicate that when residents transfer, they move to facilities with substantially fewer deficiency citations, including severe deficiencies. The number of care citations in the facility to which a patient transfers is 29.6% lower than the closing facility. Similarly, patients experience a 45.6% drop in the number of severe deficiencies. Appendix Figure B.11 documents an identical decline in total deficiencies. 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. These results are consistent with the mortality results indicating clinically meaningful benefits from patient reallocation.

Finally, 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 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.[9] 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.[10] Both log (Figure 4d) and linear (Appendix Figure B.12) 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.

4.5 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), re-

---

9. 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%.

10. 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.

placing the dependent variable with a hospitalization indicator. I also investigate the 'preventable' hospitalizations described in Section 3.3 indicative of low-quality nursing home care. These results, presented in Figure 5, reveal a substantial increase in the risk of any hospitalization following facility exit: residents face a short-run 2.84 percentage point increase in the risk of any hospitalization. Restricting to the subset of 'preventable' hospitalizations, I find a 1.13 percentage point increase in the risk of any preventable hospitalization. This corresponds to a consistent 23% relative increase across diagnosis groups, including infections, falls/inuries, and bed sores (Appendix Table B.5). Hospitalization risk eventually returns closer to its baseline rate, though remain 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.

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 (Appendix Table B.5). 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 (212.0%) and endocrinological, nutritional, and metabolic diseases (209.8%). 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.

5   Conclusion

This paper investigates the role of patient reallocation to higher performing providers in improving health care outcomes. While such reallocation is essential for quality improvement in the health care sector, there may be significant transition costs involved when providers abruptly exit. I consider both the short-run transitory costs as well as the long-run reallocative benefits in the context of 1,109 nursing home exits over a fifteen year period.

I find substantial initial costs for incumbent residents, as patients face large increases in their mortality risk in the period surrounding the closure. Yet, the firms that patients transfer to have higher quality, and this reallocation generates meaningful long-run survival benefits. Indeed, these survival benefits are significantly large that the net mortality effect is *lower* than if the exit had not occurred. Notably, these benefits are concentrated among patients living in competitive nursing home markets. Overall, these findings demonstrate the general result that there are often gains from shifting economic activity towards higher-productivity firms, but such shifts may incur significant short-term costs.

References

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

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.

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

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.

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.

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.

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2022. *Producing Health: Measuring Value Added of Nursing Homes.* Working Paper. Unpublished.

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

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

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. 2021. *Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes.* Technical report w28474. National Bureau of Economic Research.

Hackmann, Martin B, R Vincent Pohl, and Nicolas R Ziebarth. 2021. *Patient Versus Provider Incentives in Long-Term Care.* Working Paper. Unpublished.

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.

Harrington, Charlene, Helen Carrillo, Rachel Garfield, Ellen Squires Published: Apr 03, and 2018. 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.*

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.

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.

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.

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 (1982)* 68 (5): 933–940.

6   Tables and Figures

(a) Facility Mortality Preceding Exit Exit

(b) Resident Survival Following Exit
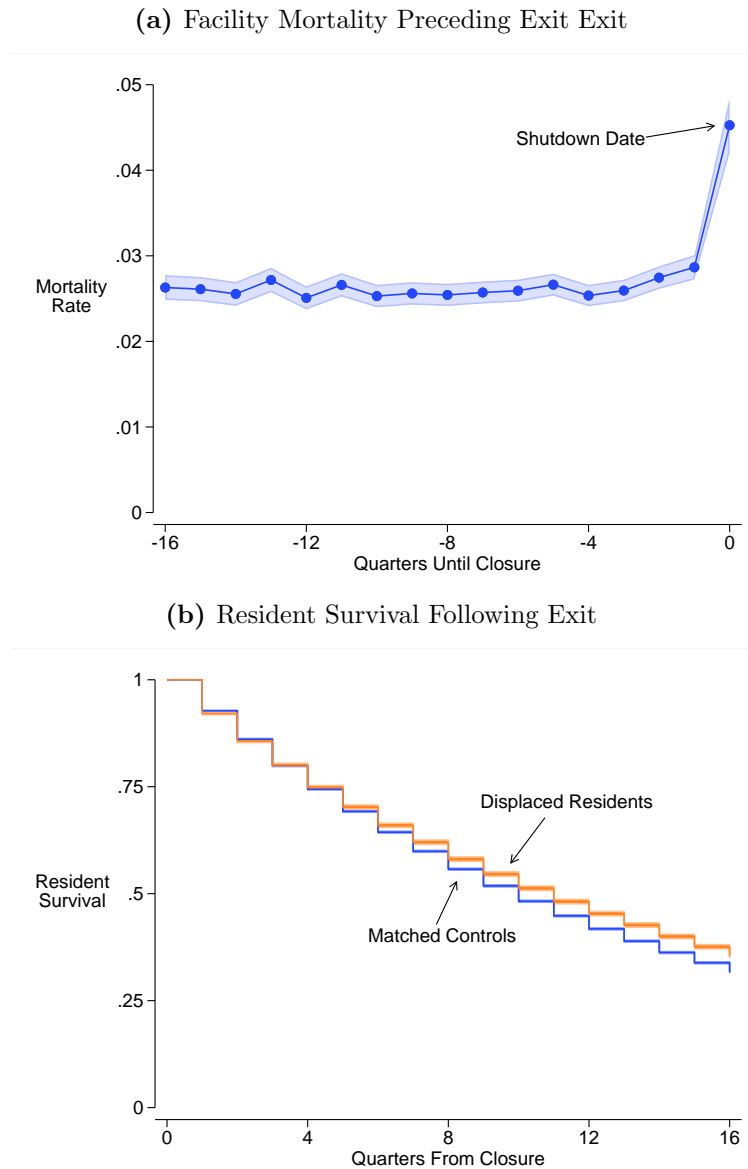
Figure 1: Preliminary Evidence on Mortality Effects of Nursing Home Exits

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.

(a) 2-Quarter Cohort: Full Sample   **(b)** 4-Quarter Cohort: Full Sample

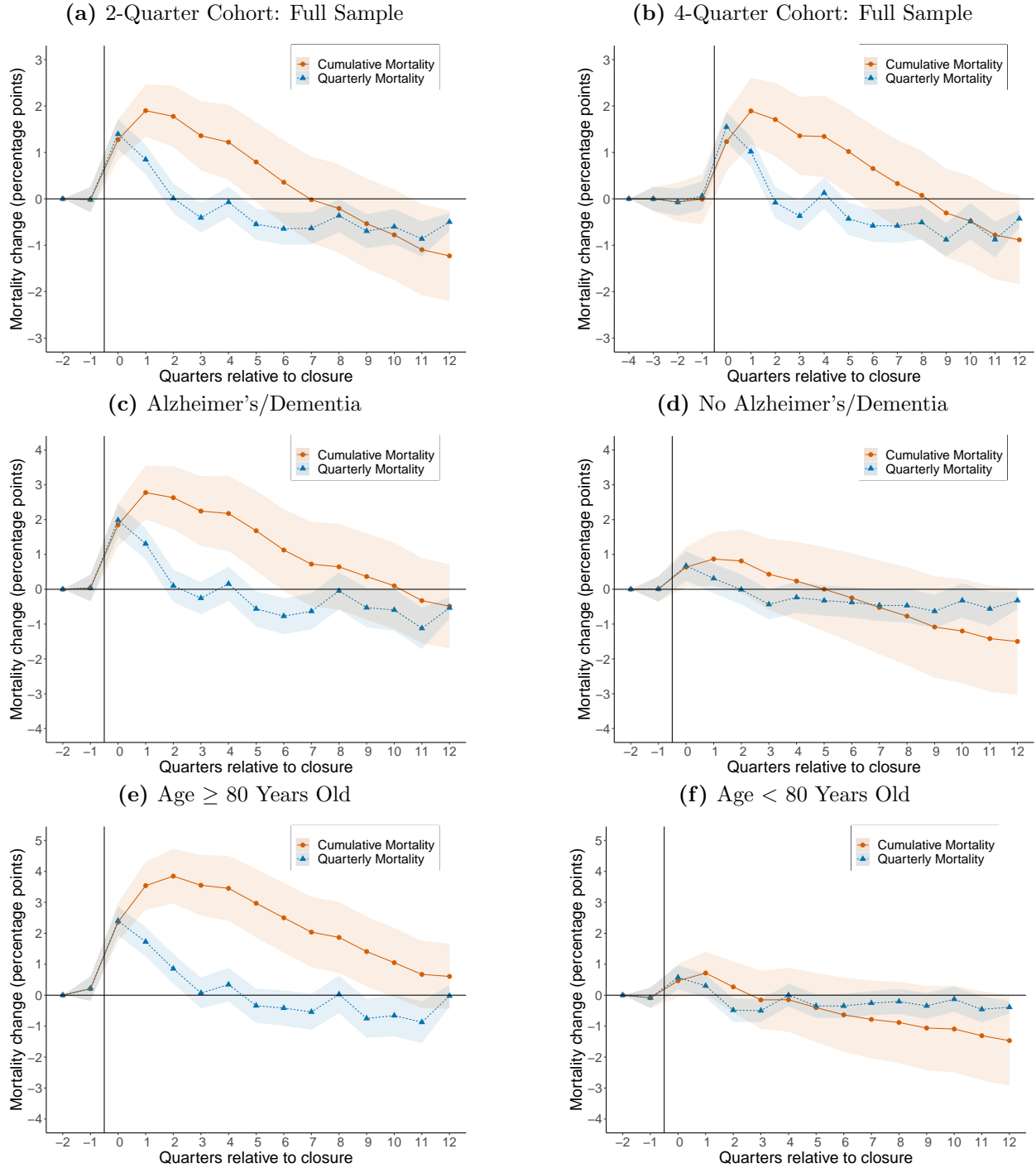**(c)** Alzheimer's/Dementia   **(d)** No Alzheimer's/Dementia

(e) Age ≥ 80 Years Old   **(f)** Age < 80 Years Old

Figure 2: 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.
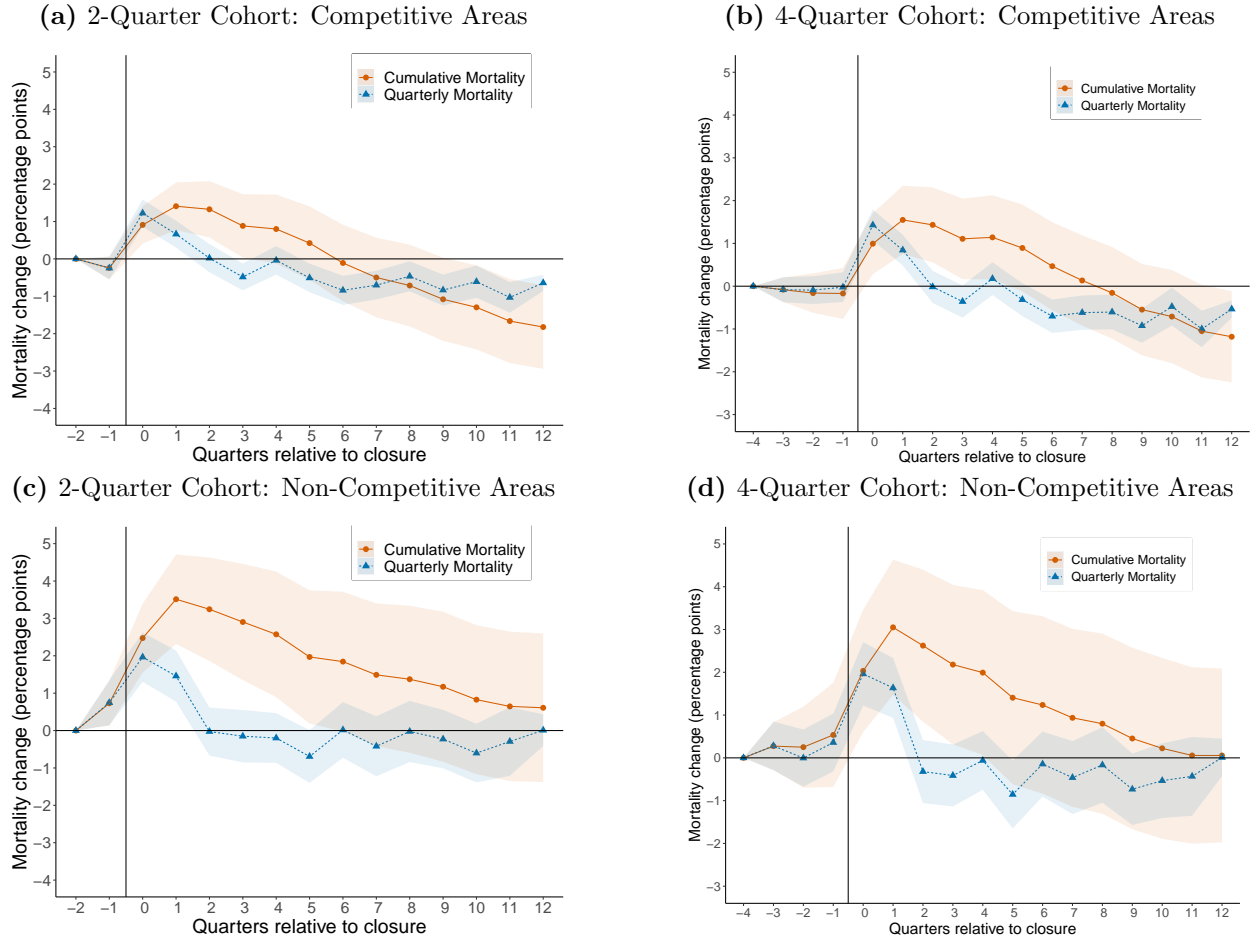
18

(a) 2-Quarter Cohort: Competitive Areas

(b) 4-Quarter Cohort: Competitive Areas

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

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

Figure 3: 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).
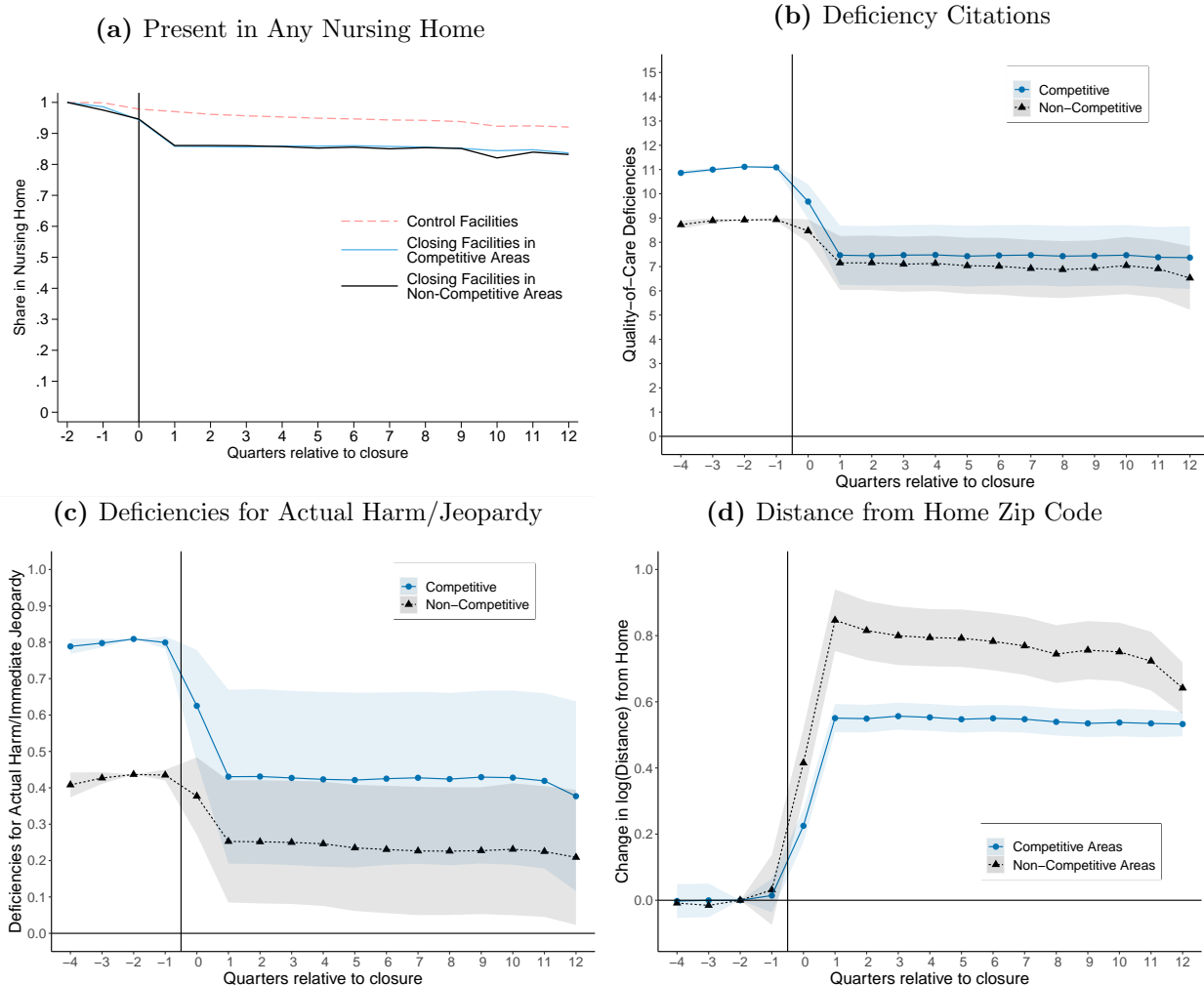
(a) Present in Any Nursing Home

(b) Deficiency Citations

(c) Deficiencies for Actual Harm/Jeopardy

(d) Distance from Home Zip Code

Figure 4: Reallocation to New Facilities

Notes: Figures present how patients reallocate following their displacement from a closing nursing home. Panel (a) calculates the empirical share of patients in each cohort who transfer to a new nursing home. Panels (b)-(d) present β^τ estimates from equation (1), with differing dependent variables. Panels (b) and (c) document the decline in the number of care-related deficiency citations for residents who are reallocated, including severe citations for patient harm. Panel (d) demonstrates how far patients are displaced following their nursing home closure, 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. In panels (b)-(d), patients who do not transfer to a new nursing home are excluded.

(a) Hospitalization Rate

(b) Preventable Hospitalization Rate

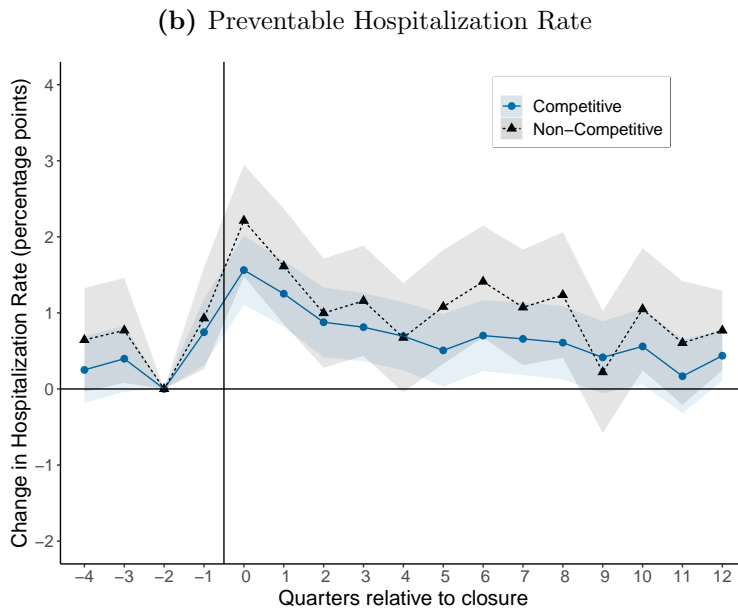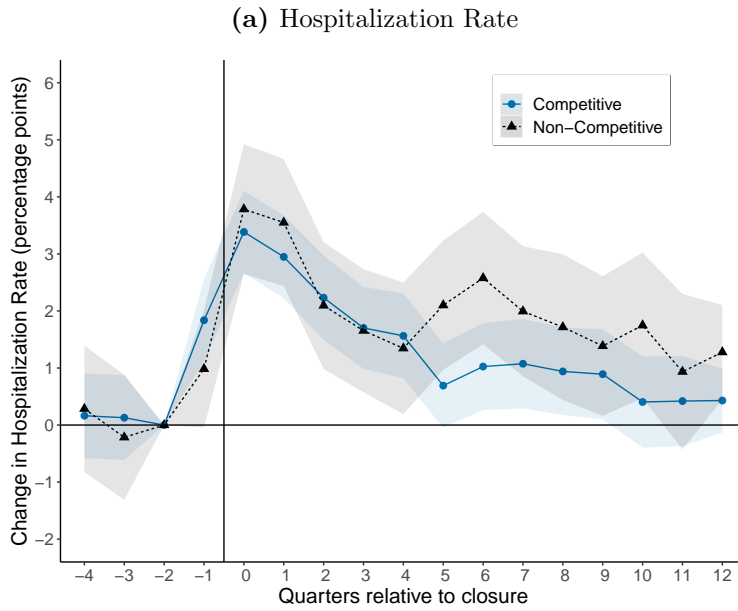**Figure 5:** Hospitalization Results

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 'preventable hospitalizations,' reflective of low quality of nursing home care.

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).

For these reasons, measuring quality is an on-going area of research: two recent papers by Einav, Finkelstein, and Mahoney (2022) and Olenski and Sacher (2022) estimate nursing home quality for short-stay patients using instrumental variable approaches. Einav, Finkelstein, and Mahoney (2022) construct a 'value-added' measure as the facility-specific component of the change in the probability of discharge back to the community, whereas Olenski and Sacher (2022) estimate a Bayesian model of quality using 90-day mortality. Both papers report considerable heterogeneity in quality across facilities. Yet, both quality measures are ill-suited for the long-stay patient population studied in this paper. By definition, long-stay patients are those who were not quickly discharged back to the community and who survived beyond the 90-day threshold. As a consequence, I rely on the more widely used quality of care violations, which are relevant to all patient populations.

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.[11] 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 1,109 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.

---

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

B Additional Tables and Figures
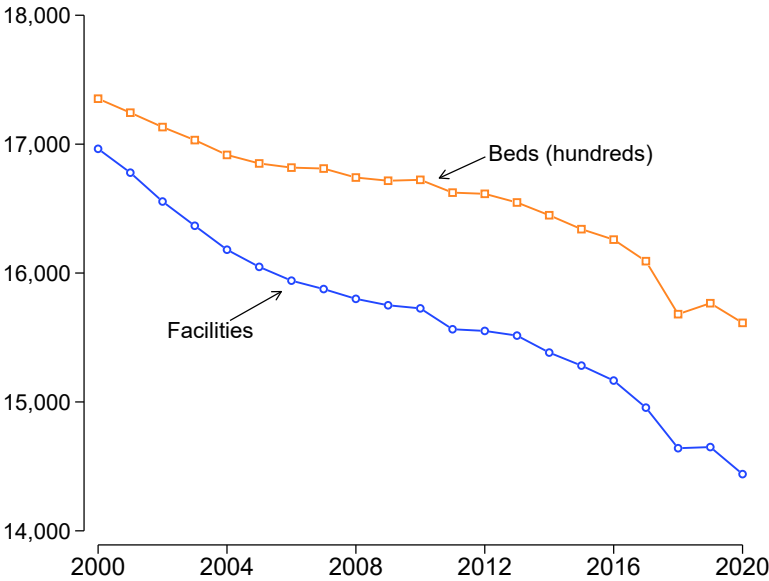
Figure B.1: Aggregate Nursing Home Reduction

Notes: Figure documents the decline in the total number of skilled nursing facilities and beds over the period 2000-2020. Data from the LTCFocus.org database. Bed counts are measured in hundreds on the same axis.
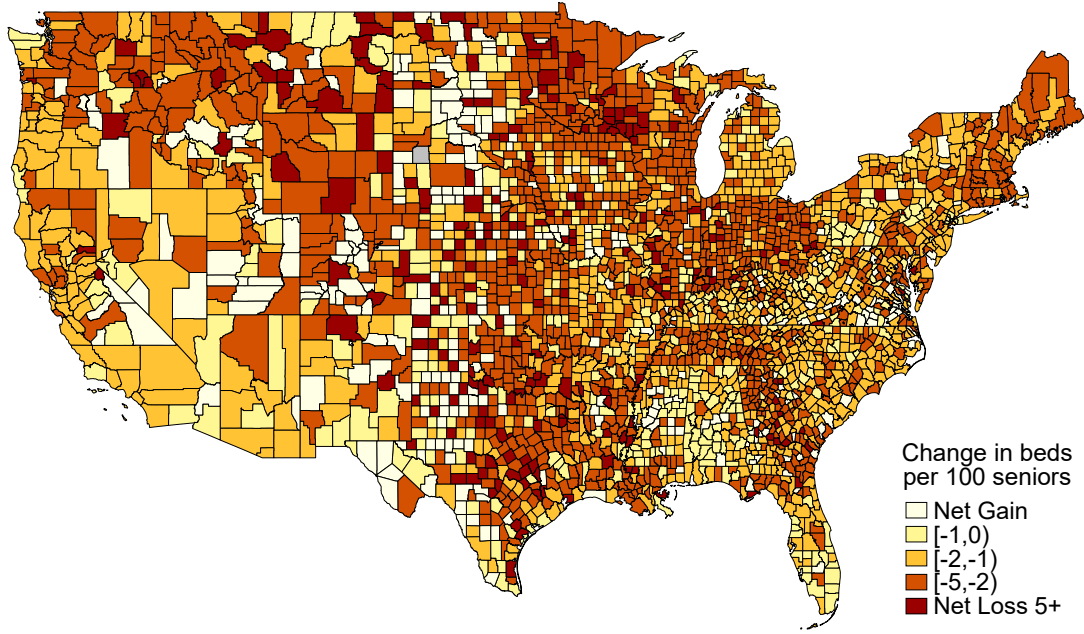
Figure B.2: Geographic Variation in Capacity Decline

Notes: Figure documents the (county-level) geographic variation in the decline of nursing home capacity over the sample period, with the sharpest reductions occurred through rural areas in the South and Midwest. Data from the LTCFocus.org database and the U.S. Census Bureau annual population estimates.
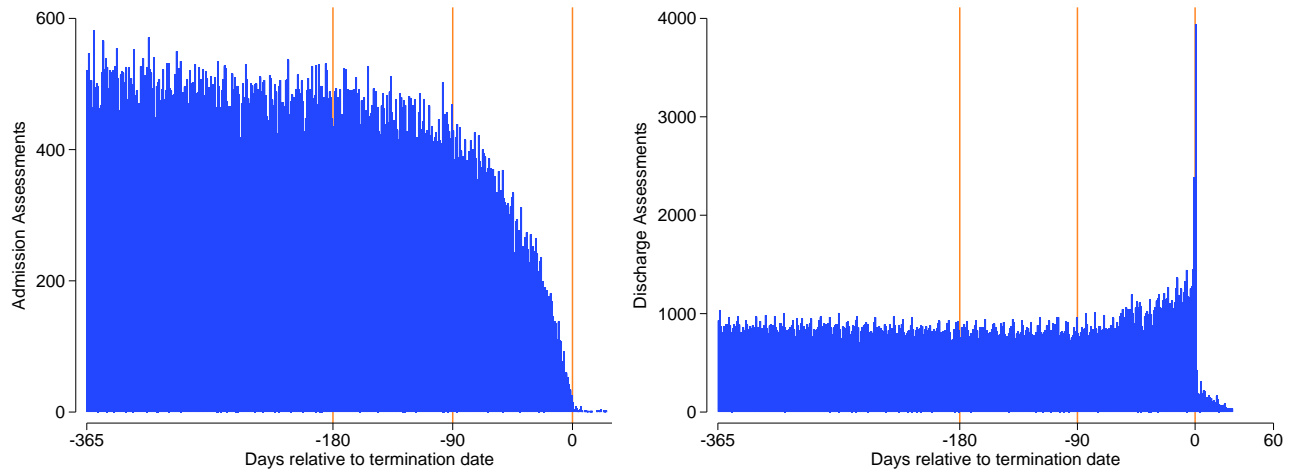
(a) Admisson Assessments

(b) Discharge Assessments
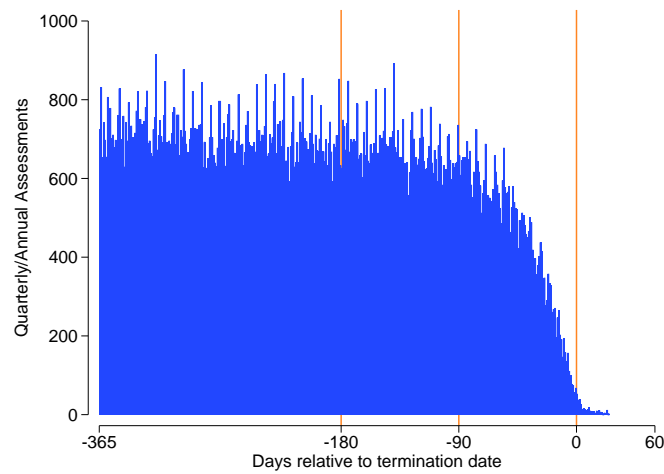
(c) Quarterly/Annual Assessments

Figure B.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.
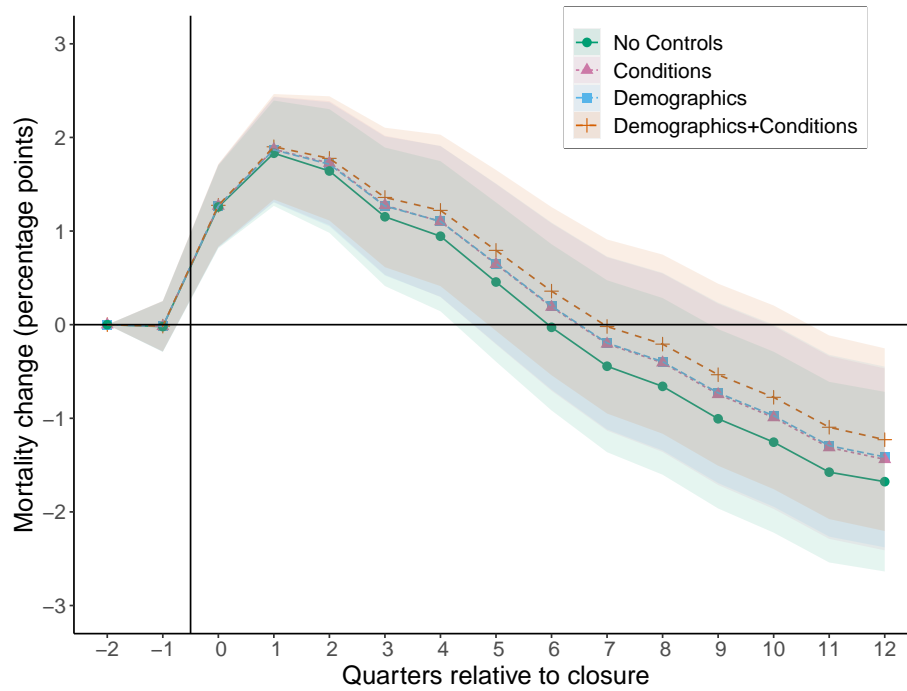
Figure B.4: Test of Coefficient Stability

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.
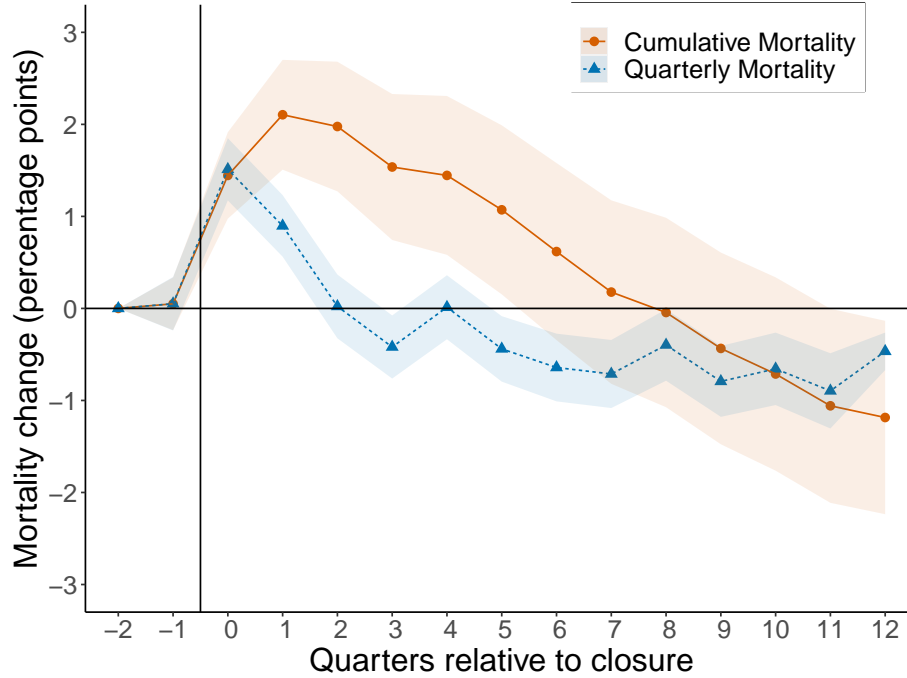
Figure B.5: Mortality effect with claims-derived controls

Notes: Figures present 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 only defined for Medicare Advantage patients, I restrict the sample to only fee-for-service Medicare enrollees.
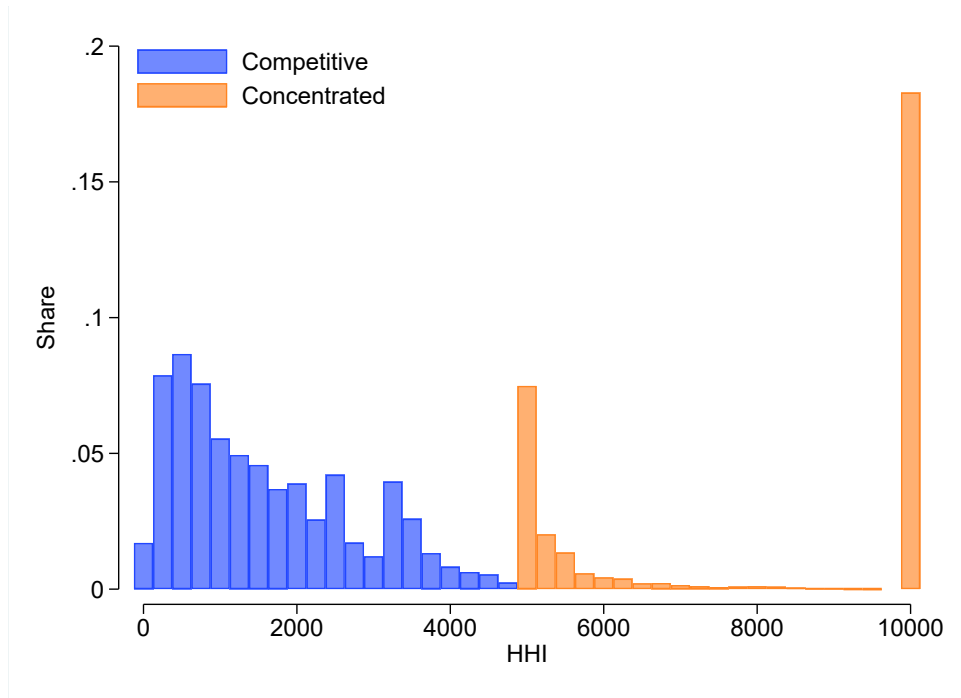
Figure B.6: Distribution of HHI in year prior to exit among analysis sample

Notes: Figure plots the distribution of facility-level Hirschman-Herfindahl Index (HHI), drawn using a 10 kilometer radius around each facility (Gandhi, Song, and Upadrashta 2020). 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 concentrated, and the remainder as competitive.
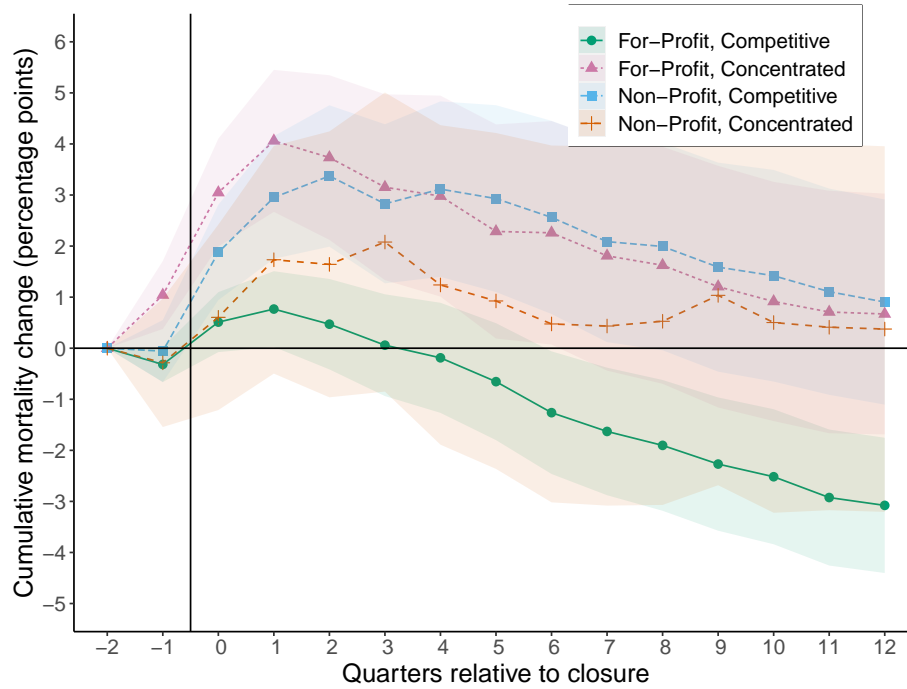
Figure B.7: Cumulative mortality by concentration and ownership status

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.

(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
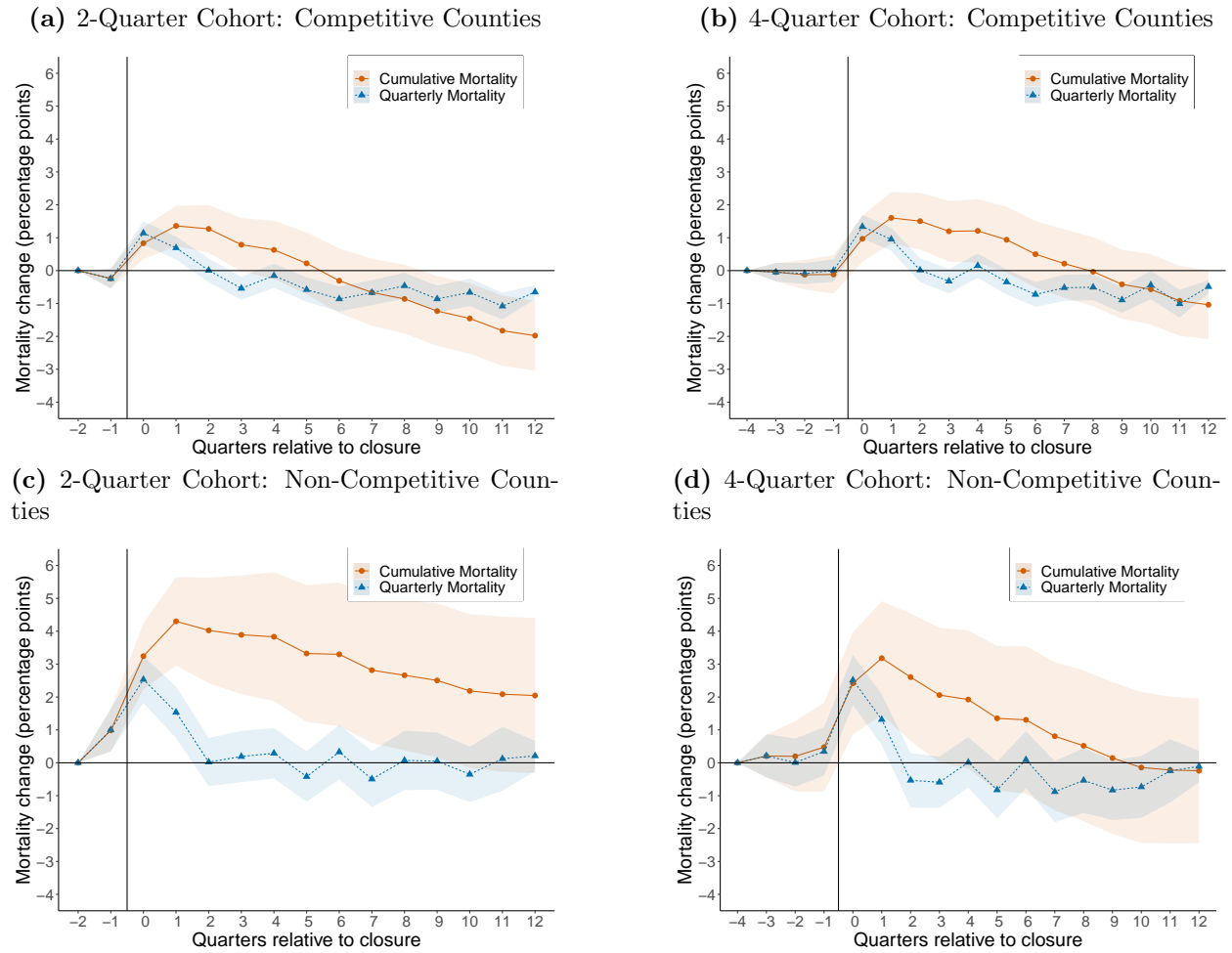
Figure B.8: Mortality change by county-level market concentration

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.
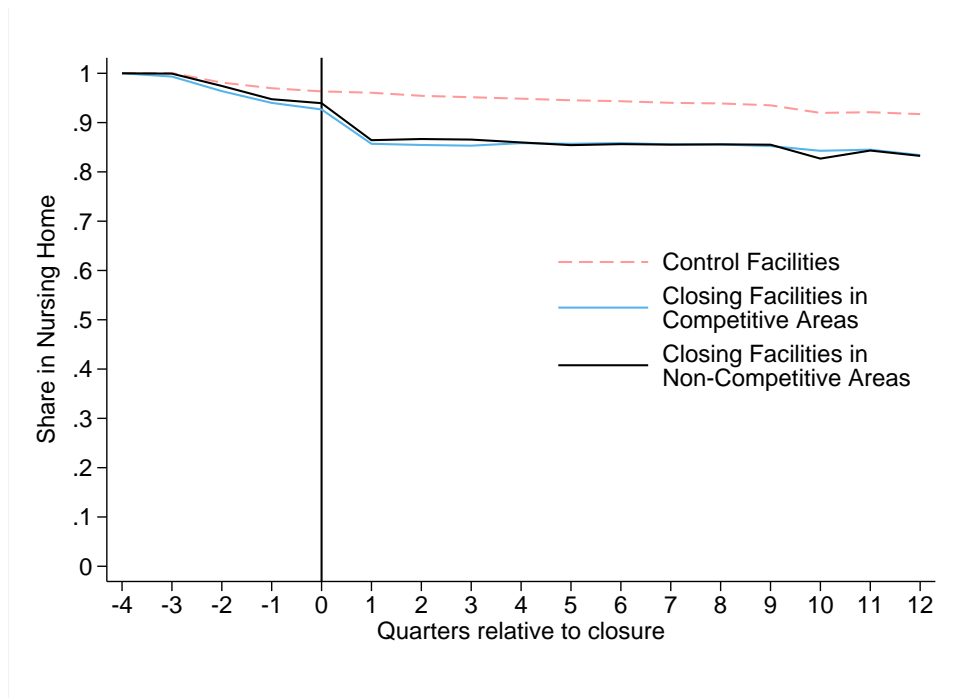
Figure B.9: Share of surviving cohort still present in a nursing home: 4-quarter cohort

Notes: Figures present the empirical share of residents who are still in a nursing home for the 4-quarter lookback cohort.
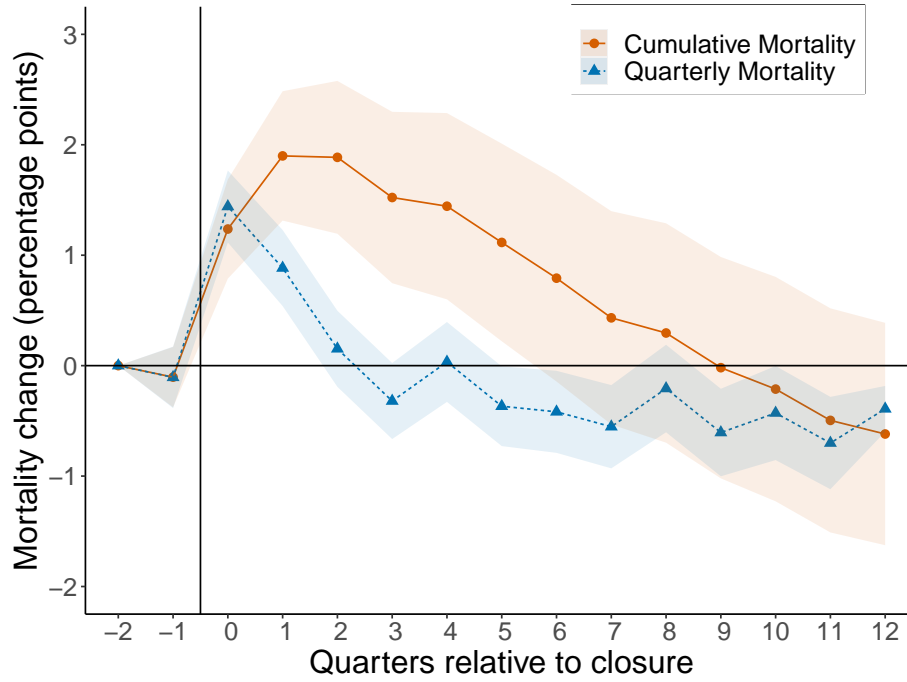
Figure B.10: Mortality rate relative to closure

Notes: Figures present 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.
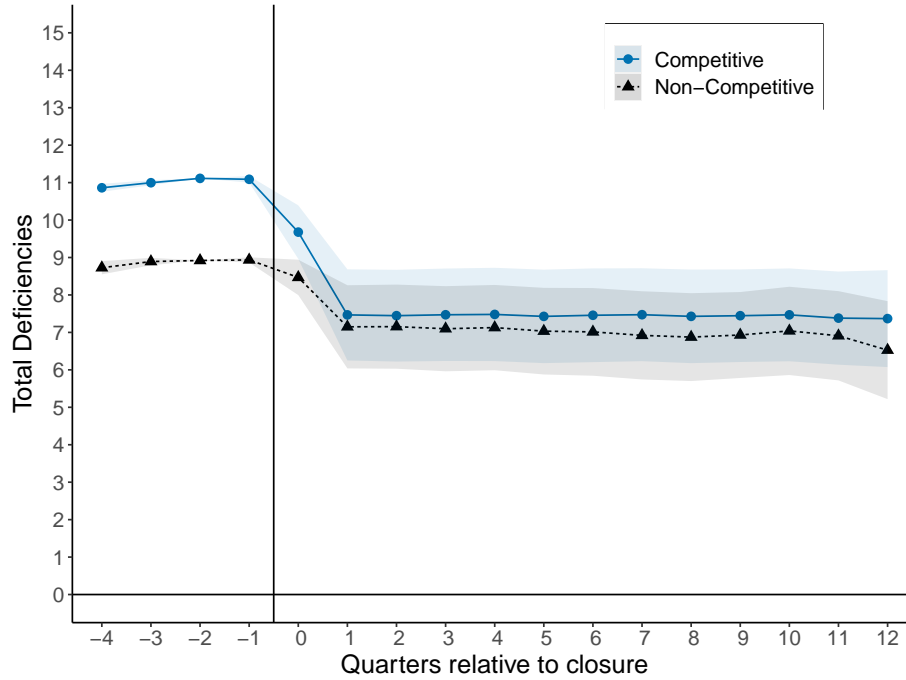
Figure B.11: Total Deficiency Citations

Notes: Figures present how patients reallocate following their displacement from a closing nursing home. This figure is the total deficiencies analogue to panels (b) and (c) of Figure **??** in the main text, which are restricted to only certain violations. Patients who do not transfer to a new nursing home are excluded.
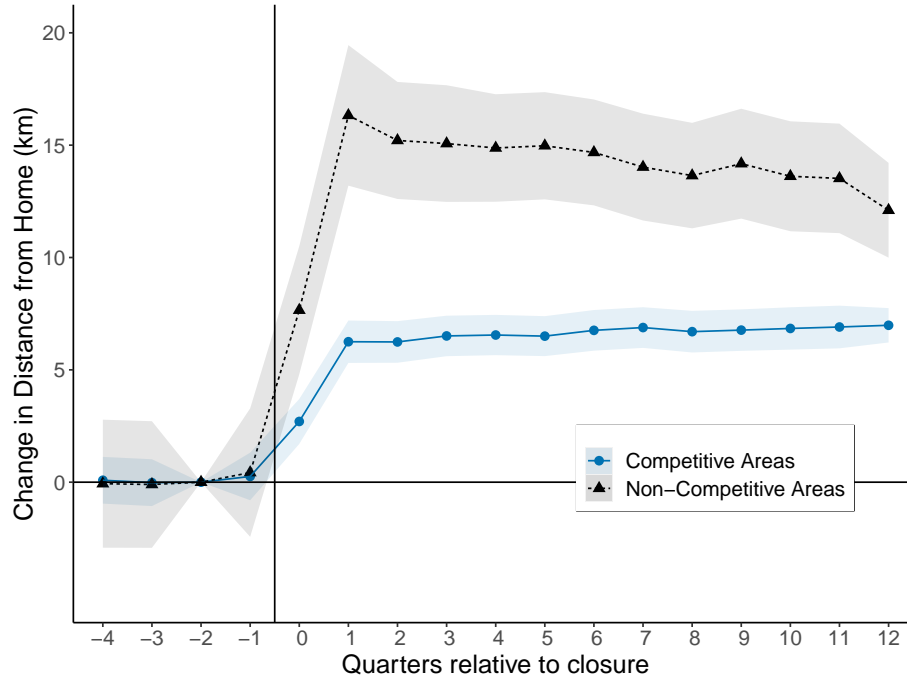
Figure B.12: Distance from home zip code

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.

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 B.1: Data Sources

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

	Closed Firms	Matched Firms	All Non-Closed Firms
	(1)	(2)	(3)
Facility Characteristics			
Total Beds	84.8	91.9	110.5
Alzheimer's Unit, %	9.0	9.5	18.9
For-Profit, %	74.5	73.3	71.9
Concentrated, %	30.8	29.5	30.6
County Population, %			
Large Central Metro	24.7	25.9	21.3
Suburban	14.8	15.1	19.9
Small/Medium Metro	28.5	28.9	30.3
Rural	32.0	30.1	28.4
Patient Characteristics, %			
Occupancy	70.4	75.8	84.8
Medicaid	74.1	71.7	63.0
Private-Pay	18.1	18.7	24.7
Profit Margin, %	-8.9	-0.8	1.8
N	1,109	3,895	197,786

Table B.2: 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. 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.

	Closing Facility (1)	Matched Facility (2)
Resident Characteristics		
White, %	78.5	80.6
Female %	65.8	69.8
Age	78.7	80.7
Medicare Advantage %	12.5	11.6
Prior Diagnoses		
Diabetes, %	30.7	31.1
Peripheral Vascular Disease, %	13.6	14.3
Alzheimer's/Dementia, %	55.7	56.8
Stroke, %	23.6	25.8
Depression, %	52.0	53.3
Hip Fracture, %	7.9	9.1
Requires Assistance		
Toileting, %	70.1	72.5
Dressing, %	71.4	72.9
Eating, %	32.3	32.5
Hygiene, %	72.1	72.5
Transfers, %	61.3	64.8
Number of Residents	43,248	204,010

Table B.3: Summary Statistics

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

	Full Sample		Competitive		Concentrated	
	(1)	(2)	(3)	(4)	(5)	(6)
β_{SR}	1.11***	1.14***	1.05***	1.08***	1.31***	1.36***
	(0.12)	(0.12)	(0.14)	(0.14)	(0.26)	(0.26)
β_{LR}	-0.51***	-0.46***	-0.49***	-0.44***	-0.58**	-0.52**
	(0.08)	(0.08)	(0.09)	(0.09)	(0.18)	(0.18)
ΔM_1	1.83***	1.90***	1.34***	1.41***	3.43***	3.51***
	(0.29)	(0.29)	(0.32)	(0.33)	(0.61)	(0.61)
ΔM_4	0.94*	1.22**	0.55	0.80	2.20**	2.57**
	(0.41)	(0.41)	(0.47)	(0.47)	(0.85)	(0.86)
ΔM_8	-0.66	-0.21	-1.13*	-0.71	0.79	1.37
	(0.48)	(0.49)	(0.55)	(0.56)	(0.99)	(1.00)
ΔM_{12}	-1.68***	-1.23*	-2.24***	-1.82**	0.06	0.61
	(0.49)	(0.50)	(0.56)	(0.57)	(1.00)	(1.01)
N	3,577,643	3,577,643	2,819,126	2,819,126	758,517	758,517
Dep. Var Mean	6.27	6.27	6.13	6.13	6.76	6.76
Controls	Base	Full	Base	Full	Base	Full

Table B.4: 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 (relative quarters 0-1) and long-run (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.

	Baseline, %	Short-Run		Long-Run	
		β	Percent β	β	Percent β
	(1)	(2)	(3)	(4)	(5)
Any Hospitalization	13.33	2.84 (0.19)***	21.3 (1.4)***	0.55 (0.17)**	4.1 (1.3)**
Any Preventable Hospitalization	5.04	1.13 (0.12)***	22.5 (2.3)***	0.22 (0.09)*	4.4 (1.8)*
Preventable Hospitalization					
Infections	3.23	0.74 (0.10)***	22.9 (3.0)***	0.06 (0.07)	1.8 (2.3)
Falls/Injuries	1.04	0.24 (0.04)***	23.4 (4.0)***	0.14 (0.03)***	13.5 (2.7)***
Nutrition/Hydration	0.37	0.08 (0.03)**	22.4 (8.0)**	0.02 (0.02)	6.7 (5.4)
Bed Sores	0.35	0.08 (0.03)**	23.2 (8.2)**	0.00 (0.02)	0.5 (5.7)
Psychosis	0.19	0.04 (0.02)*	23.2 (11.4)*	0.00 (0.02)	1.3 (8.5)
Any In-hospital Death	0.32	0.28 (0.05)***	87.1 (16.0)***	-0.07 (0.03)**	-21.4 (7.9)**
In-hospital Death with Diagnosis					
Infectious/Parasitic Diseases	0.04	0.08 (0.02)***	212.0 (46.5)***	-0.01 (0.01)	-17.9 (26.4)
Respiratory System	0.08	0.07 (0.02)**	79.7 (30.1)**	-0.01 (0.01)	-12.8 (14.0)
Endocrine/Nutritional/Metabolic	0.01	0.03 (0.01)**	209.8 (76.9)**	0.00 (0.00)	-19.0 (33.8)
Kidney/Urinary Tract	0.02	0.02 (0.01)	100.9 (56.8)	-0.01 (0.01)*	-52.4 (25.1)*
Digestive System	0.02	0.02 (0.01)	82.0 (72.2)	-0.01 (0.01)	-40.6 (31.4)
Musculoskeletal	0.01	0.01 (0.01)	111.6 (87.9)	0.00 (0.00)	-18.0 (39.3)
Nervous System	0.02	0.00 (0.01)	29.6 (64.9)	-0.01 (0.00)	-56.8 (31.4)
Circulatory System	0.05	-0.01 (0.02)	-22.6 (36.7)	-0.01 (0.01)	-26.5 (17.6)

Table B.5: 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.