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

Andrew Olenski*

Department of Economics
Columbia University

November 4, 2022

LINK TO LATEST VERSION

Abstract

This paper examines the impacts of health care provider exits on patient outcomes and subsequent reallocation. Using administrative data on the universe of nursing home patients, I estimate the mortality effects of 1,109 nursing home closures on incumbent residents with a matched difference-in-differences approach. I find that displaced residents face a short-run 15.7% relative increase in their mortality risk. Yet this increase is offset by long-run survival improvements, so the cumulative effect inclusive of the initial spike is a net decline in mortality risk. These gains are driven by patients reallocating to higher quality providers. I also find significant heterogeneity by local market conditions: the survival gains accrue only to patients in competitive nursing home markets, whereas residents in concentrated markets experience no survival improvements. I then develop and estimate a dynamic model of the nursing home industry with endogenous exit. Combining the structural estimates with the reduced form mortality results, I examine the effects of two counterfactual reimbursement policy experiments on nursing home closures and resident life expectancy. A universal 10% increase in the Medicaid rate decreases the frequency of closures, but causes some low-quality providers to remain open in competitive areas. In contrast, targeted subsidies for facilities in areas with limited alternatives improves overall life expectancy by averting the costliest nursing home closures.

*I am particularly thankful to my Ph.D. advisers Pietro Tebaldi, Ashley Swanson, Adam Sacarny, Gautam Gowrisankaran, and Suresh Naidu for their many helpful comments. I am also grateful to Ashvin Gandhi, David Grabowski, John Bowblis, Michael Best, Sandy Black, Bentley MacLeod, David Molitor, Anupam Jena, Szymon Sacher, and many seminar participants at Columbia and ASHEcon for their assistance and feedback. I would also thank Mohan Ramanujan, Elizabeth Adams, and Maurice Dalton for their help in obtaining and managing the data. Finally, I gratefully acknowledge support from the National Science Foundation Graduate Research Fellowship.

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 the efficacy of alternative payment reforms to avert further closures.

Nursing home closures may entail countervailing forces for incumbent residents. On one hand, patients who are displaced may be expected to 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 members of an already vulnerable population. Conversely, it is plausible that facilities that exit due to financial fragility may have lower quality than replacement-level alternatives, and so displaced residents who are reallocated may find themselves in higher quality facilities, thereby improving health outcomes and extending their longevity. Understanding these effects is therefore crucial to assessing the desirability of alternative policies aimed at sustaining financially vulnerable nursing homes.

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. To evaluate the effects of alternative reimbursement policies on firm closures, I then estimate a dynamic model of the nursing home's exit decision, and combine these structural estimates with the reduced form mortality results to evaluate the effects of such policies on resident life expectancy.

I find that residents of nursing homes that close experience a 1.14 percentage point increase in their short-run risk of mortality, representing a dramatic 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 present evidence that the exiting facilities are of particularly low quality, and that surviving patients reallocate to higher-quality firms, as measured by state-issued deficiency citations.

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 exiting non-profits (which tend to have higher quality) generate no survival improvements.

This disparity in outcomes between areas with robust nursing home markets and areas with declining access to care raises the question of how to balance the implied access-quality tradeoff. To this end, I develop and estimate a dynamic model of nursing home exits, with the goal of evaluating alternative reimbursement policies. The demand side of the model resembles Hackmann (2019), who develops a rich, static industry model of nursing home supply and demand with the aim of examining how changes to reimbursement rates impact the equilibrium levels of nurse staffing. I extend this model to incorporate a dynamic exit decision in the style of Pakes, Ostrovsky, and Berry (2007). Using the model estimates, I then examine how changes in the Medicaid reimbursement rate affect the number and distribution of nursing home closures. Combining these results with the reduced form mortality estimates, I can then evaluate the effects of alternative reimbursement policies on resident mortality.

I find that a universal 10% increase in the Medicaid reimbursement rate reduces the observed number of closures, yet it does so in both competitive markets, where I find reallocative benefits, as well as in concentrated markets, where I find no evidence of survival gains. This result motivates a more flexible counterfactual policy experiment, which narrowly targets the subsidies to different firms according to their observable characteristics. Such a program is similar in spirit to the existing federal Rural Hospital Flexibility program, which boosts reimbursement rates for financially vulnerable hospitals that provide critical access care in rural areas. Targeting higher rate increases only to firms in areas with few other providers, while avoiding the rate increases for firms in competitive areas, generates a more favorable distribution of firm exits, by continuing to permit the beneficial exits in competitive areas. However, I do find that patients value the access to care provided even by firms in competitive areas, and so there is a quality-access trade-off present even with the more targeted subsidy.

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 2019; 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 some of the most vulnerable in the health system, and their health status is particularly fragile. 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). In addition to modeling the mortality consequences of firm exits, I also examine how changes

in reimbursement rates would affect the distribution of firm 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. My counterfactual analyses are closely related to Hackmann (2019), who develops a rich model of the nursing home industry and examines the role of the Medicaid reimbursement rate in determining staffing levels, a common measure of quality. I adapt Hackmann's demand model and estimation procedure to my setting, and extend his supply side to incorporate the firm's dynamic exit decision.

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. Sections 3 and 4 present the reduced form research design and mortality results, respectively. Section 5 describes the structural model of the nursing home exit decision, and Section 6 details the estimation procedure and presents results. In Section 7, I use the model estimates combined with the reduced form results to analyze the mortality effects of several reimbursement policies designed to avert nursing home closures. Section 8 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 routing 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.

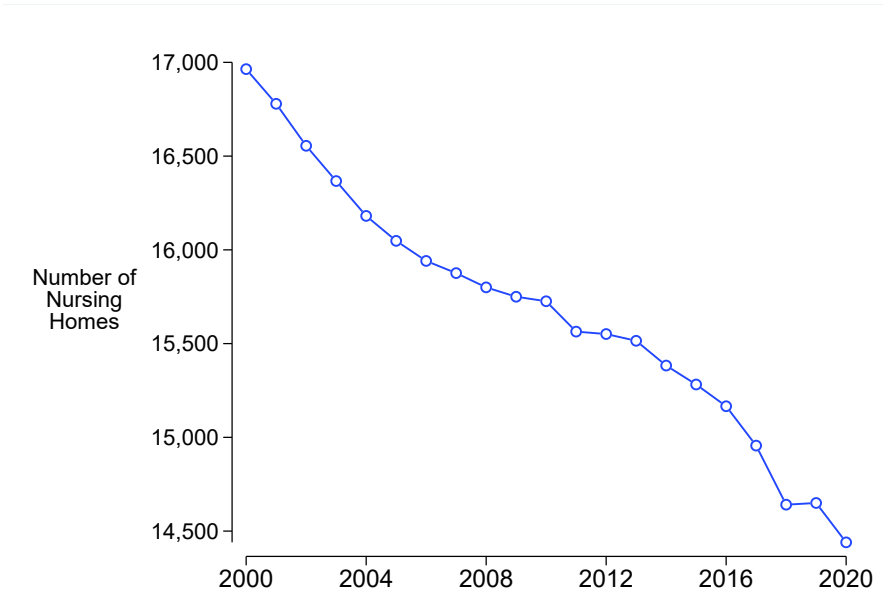
2.1 Recent Trends in U.S. Nursing Home Entry and Exit

The nursing home industry is a substantial component of the economy. Comprising approximately 1% of U.S. gross domestic product 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.

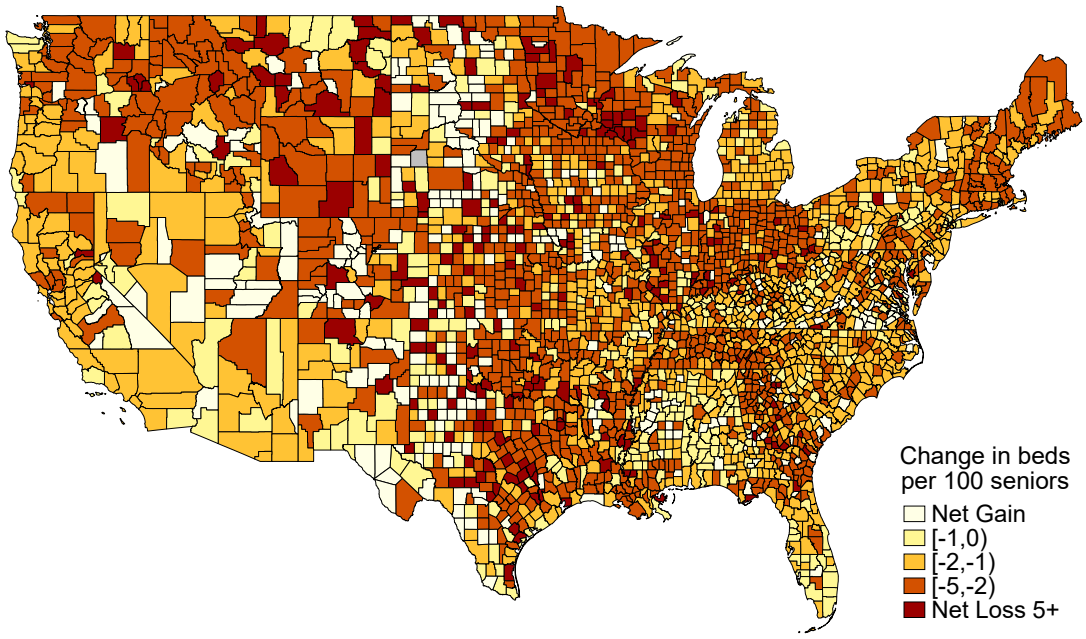
Despite the market's size and aging demographics, the nursing home industry has been marked by an aggregate decline over the past few decades. The top panel of Figure 1 documents that from 2000 to 2019, the total number of facilities shrank 13.6% from 16,964 to 14,650 (data from LTCFocus.org), even as 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. The bottom panel of Figure 1 documents that 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. 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. 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). I replicate these results using an annual panel of nursing homes from 2011 to 2019, and present the results in Figure 2. As expected, I find that firms with higher occupancy rates and lower shares of Medicaid patients report higher profits, and that the exit probability is a decreasing function of profits. To ease comparison, I scale variable profits by facility size (number of beds).

The dependence of private facilities on the Medicaid rate underscores that the majority of nursing home care is publicly financed. In this respect, the nursing home market is exceptional even relative to the rest of the U.S. health care sector. Medicare (the near-universal health insurer for the elderly and disabled) and Medicaid (the means-tested 'safety net' insurer) together account for approximately 85% of annual revenues for nursing home care (Gandhi 2020). In contrast, public payers comprise just under half of patient revenues in the hospital industry. The outsized role of Medicaid is owed to the fact that Medicare reimbursement for nursing home stays is capped to only the first 100 days of a stay, meaning that most long-term patients end their stays on Medicaid, after their assets have been depleted.



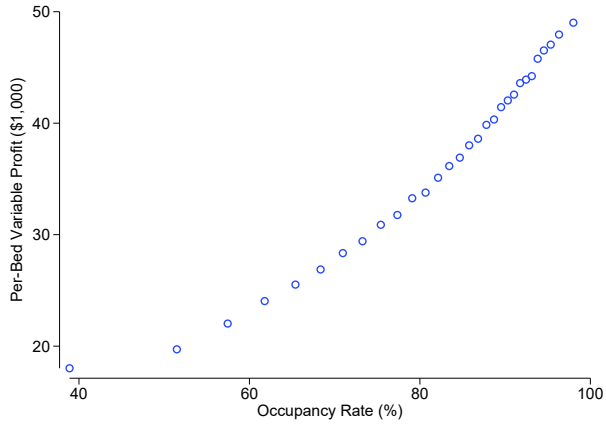
(a) Aggregate Nursing Home Reduction



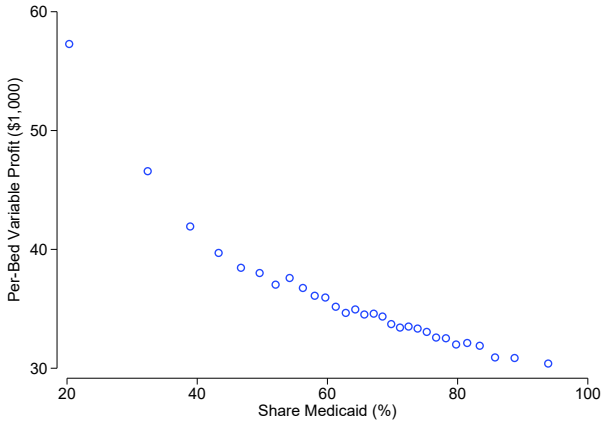
(b) Geographic Variation in Capacity Decline

Figure 1: Contraction in the Nursing Home Industry

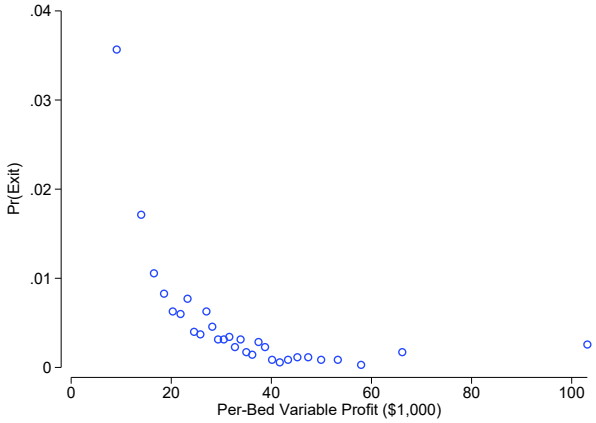
Notes: Top panel documents the decline in the total number of skilled nursing facilities over the period 2000-2020. Bottom panel documents the (county-level) geographic variation in the decline of nursing home capacity over the sample period, with the sharpest reductions occurred through rural areas in the South and Midwest. Data from the LTCFocus.org database and the U.S. Census Bureau annual population estimates.



(a) Variable Profits by Occupancy Rate



(b) Variable Profits by Medicaid Share



(c) Exit Rate by Variable Profit

Figure 2: 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 2.3.2.

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.

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 annual 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, nursing home quality of care is an inherently difficult object to measure, and the deficiency citations studied here 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.

2.3 Data

2.3.1 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. 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 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. 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.[1] In estimating the supply-side of the structural model detailed in Section 5, I collect national accounting data on revenues and variable costs from the Healthcare Provider Cost Reporting Information System (HCRIS), commonly referred to as the Medicare cost reports. I estimate the demand side of the model using MDS admission assessments in Illinois. I augment these micro-data with state Medicaid cost reports, from which I infer daily Medicaid and private rates using data on revenues and quantities (Huang and Hirth 2016). All data sources used, their years spanned, and their application in this project are summarized in Appendix Table C.1.

2.3.2 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

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

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.[2] 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.

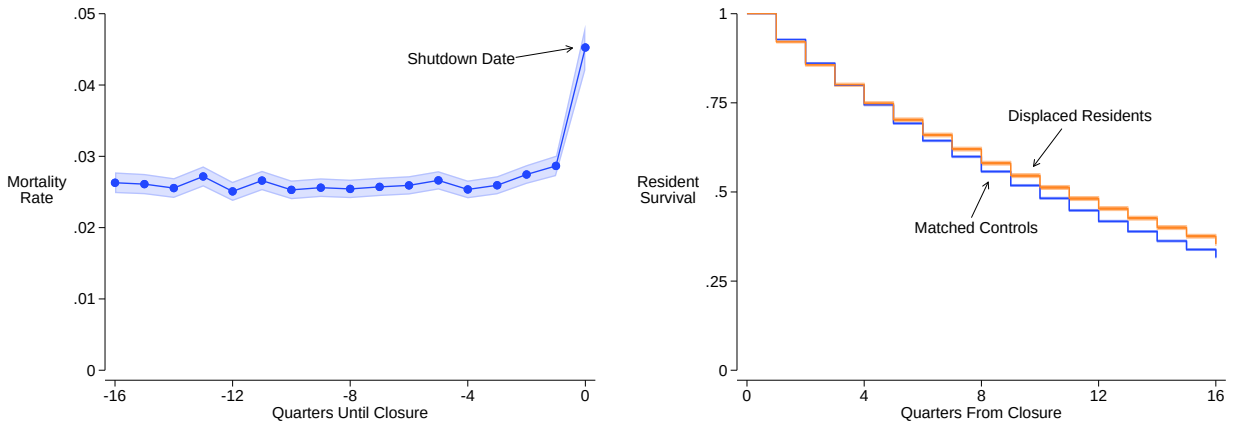
2.4 Exit and Mortality: Preliminary Evidence

Figure 3 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. Yet identifying the effect of an nursing home exit – rather than 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 3 panel (b). I also plot the corresponding survival curves for a matched control sample, consisting of residents of 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 trends *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. Nursing home closures are associated with a substantial increase in quarterly resident mortality. However, long-run survival for displaced patients trends above the corresponding survival for residents unaffected by a closure. Estimating the relative magnitudes of these two effects, and exploring

2. 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) Facility Mortality Preceding Exit

(b) Resident Survival Following Exit

Figure 3: 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 the residents displaced from the exits, relative to a matched control sample of residents of facilities that did not exit. The matching is described in Section 3.

the mechanisms behind any quality-improving reallocation, require a formal empirical strategy to identify the causal effect of nursing home exit.

3 Estimating the Mortality Effects of Exit

3.1 Research Design and Estimation Sample

Estimating the causal effect of a nursing home exit 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. This approach mirrors recent studies of the effects of provider exits on patient outcomes (e.g. Sabety 2019).

To construct the control group, I match each exiting facility with up to four control facilities on the similarity of their characteristics (measured with Mahalanobis distance) in the year prior to exit. These covariates include 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 C.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 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' shutdown decisions – which may be endogenous to demand (Figure 2 indicates 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. 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 begin to taper (Appendix Figure C.1). 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 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.

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

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).

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

	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 1: 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.

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.

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

regression:

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

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

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

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.[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

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).

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 annual rate of quality-of-care deficiencies (scaled by bed size), as well as the likelihood of any severe violations (causing patient harm or immediate jeopardy). 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.

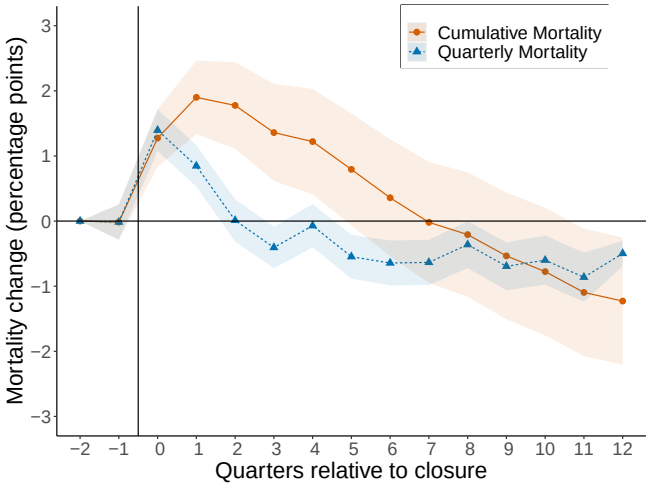
Hospitalization – In addition to the nursing home assessment data, I also observe the universe of short-stay acute care admissions for the 88.3% of my sample who are enrolled in fee-for-service Traditional Medicare, rather than a Medicare Advantage plan. Restricting my analysis to this subsample, I can 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.

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. 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.

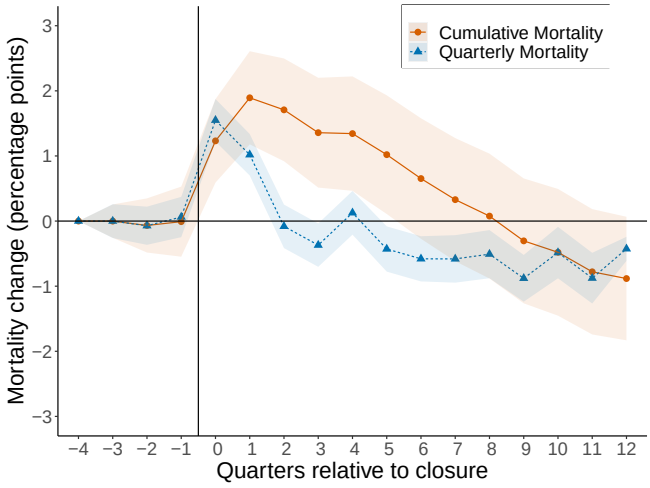
4 Mortality Results

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 4 and summarized in Table 2. The top panel of Figure 4 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



(a) Residents in facility 2 quarters prior to closure



(b) Residents in facility 4 quarters prior to closure

Figure 4: 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. The top panel presents the results for the main sample: residents in a facility two quarters prior to exit. The bottom panel presents results for residents who were in the facility four quarters prior to the closure date, allowing for comparison of parallel trends between the treatment and control groups.

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. The bottom panel of Figure 4 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.

Where do displaced residents go? In Appendix Figure C.2, I calculate the share of the surviving cohorts who remain in any nursing home by quarter. 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 C.3. I find that the mortality trends look similar in this subgroup of transferred patients, though the effects are somewhat attenuated.

Patient Heterogeneity — 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 Appendix Figure C.4. 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: 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 (Appendix Figure C.5).

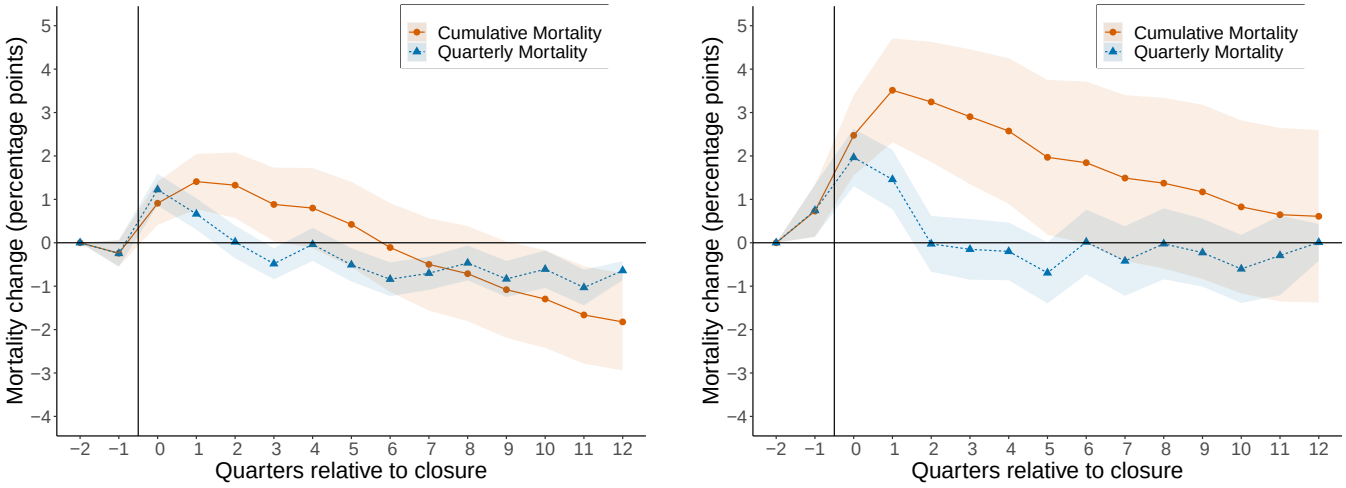
Robustness — To assess the importance of risk-adjustment (the patient-level covariates X_{it} in equation (1)), I estimate several cumulative mortality effects, iteratively adding more patient covariates. The stability of these results across specification, shown in Appendix Figure C.6 (which omits the 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 C.7. These results suggest that concern over the residual imbalance indicated by Table 1 is minimal.

4.2 Heterogeneity by Market Concentration

In light of the concerns over rural nursing home access detailed in Section 2.1, and the geographic differences in nursing home contraction demonstrated in the bottom panel of Figure 1, 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 C.8. Approximately 25% of facilities are at least duopolists (HHI $\geq 5,000$); these facilities are defined as operating in concentrated 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 (1.08 percentage points), and by 12 quarters after closure have a cumulative mortality probability that is 1.82 percentage points

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 C.10 demonstrates that using a more standard county-level HHI measure generates nearly identical results.



(a) Competitive Markets **(b)** Concentrated Markets

Figure 5: Mortality change by market concentration

Notes: Figures present the results from estimating equation (1) for the baseline cohort. 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. The top panel presents the results for residents of facilities in competitive markets (pre-closure HHI below 5,000). The bottom panel presents results for residents of facilities in concentrated markets (pre-closure HHI above 5,000).

lower. Conversely, residents of facilities in concentrated markets 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 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 C.9.[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.

4.3 Reallocation Across Facilities

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 compute the number of 'quality of care' deficiency citations per bed. These citations correspond to care-related violations (such as nursing, rehabilitation, or pharmacy) rather than, for instance, fire

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

	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

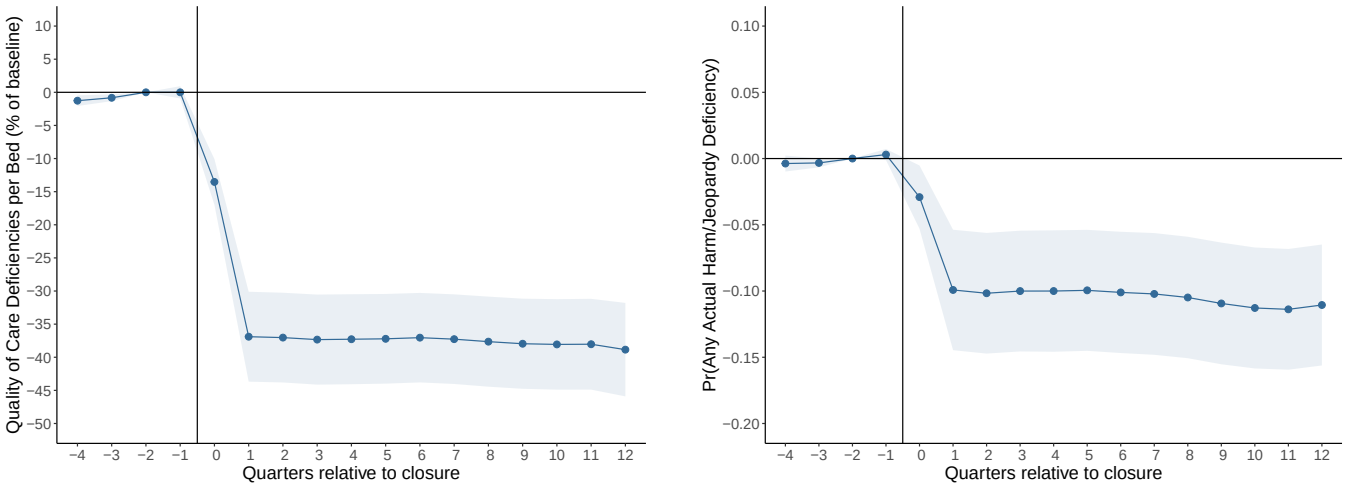
Table 2: Short-run and Long-run Mortality Effects of Nursing Home Closures

Notes: Table summarizes the main mortality effects of nursing home closures. Top panel summarizes the mortality hazards β into short-run (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.

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.

These results, documented in Figure 6, indicate that when residents transfer, they move to facilities with substantially fewer deficiency citations, including severe deficiencies. The rate of care citations per bed in the facility to which a patient transfers is 36.9% lower than the closing facility. Similarly, patients experience a 9.92 percentage point drop in the likelihood of any severe deficiency, from a baseline rate of 33.1%. Appendix Figure C.12 documents an identical decline in the rate of total deficiencies. These results are consistent with the mortality results indicating substantial 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



(a) Quality of Care Deficiency Citations **(b)** Any Actual Harm/Immediate Jeopardy Citation

Figure 6: Changes in Deficiency Citations

Notes: Figures present how patients reallocate following their displacement from a closing nursing home. Both panels present β^{τ} estimates of equation (1), with the dependent variable replaced with a measure of facility quality. Panel (a) shows the reduction in the number of 'quality of care' deficiencies per bed. Panel (b) documents the decline in the probability of at least one severe deficiency citation for placing a resident in actual harm or immediate jeopardy. Patients who do not transfer to a new nursing home are excluded.

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 7) and linear (Appendix Figure C.13) 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.

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.

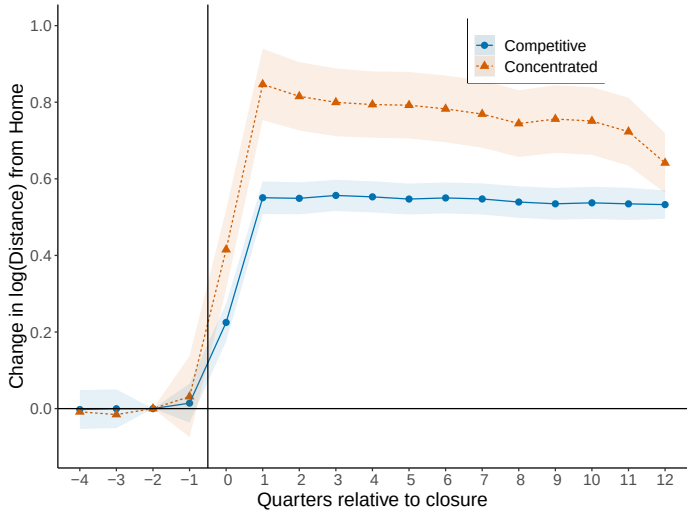


Figure 7: Distance from home zip code

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.

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 using a slightly condensed version of regression equation (1).

To examine changes in overall hospitalization risk, I estimate an analog of equation (1), replacing the dependent variable with a hospitalization indicator, and collapsing the relative time indicators into short-run (relative quarters 0-1) and long-run (2+ quarters following closure). In addition to the 'preventable hospitalizations' described in Section 3.3, I also examine in-hospital deaths with a variety of different conditions. These results are summarized in Table 3, and the event study for the risk of any hospitalization is also plotted in Appendix Figure C.11.

These results 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 among long-stay nursing home residents (Walsh et al. 2012), I estimate a 1.13 percentage point increase in the risk of any preventable hospitalization. This corresponds to a consistent 23% relative increase across diagnosis groups,

	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 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.

including infections, falls/inuries, and bed sores. In the long-run (two or more quarters following facility closure), hospitalization risks return much closer to their baseline levels, though do remain slightly elevated. These results are consistent with declines in facility quality during the period of the closure, in addition to the potential tr

Turning to changes in within-hospital death, which I use to approximate cause-of-death as this is not recorded in the MDS assessments, 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. As before, the prevalence of these conditions are consistent with the provision of inadequate nursing care during the period of the closure.

5 Empirical Model of Nursing Home Exits

Motivated by the evidence on the consequences of nursing home closures on incumbent resident mortality and subsequent reallocation, I turn next to an empirical model of the nursing home

industry with endogenous firm exit. In the model, nursing homes observe patient demand and current variable profits, and decide whether to pay a fixed cost of staying or to permanently exit.[11] The estimated model allows me to examine how counterfactual reimbursement policies would impact the number of nursing home exits, as well as to compute their implied effects on consumer surplus. Moreover, by combining the structural model with the mortality effects estimated in Section 4, I am able to evaluate the distributional impacts of these counterfactual reimbursement policies on resident life expectancy.

5.1 Primitives

In every period (year) t, a set J_t of nursing homes is active, and each $j \in J_t$ decides the price charged to private patients, P_{jt}. Each nursing home j is also characterized by a number of observable quality-of-care deficiencies W_{jt}, and by a per-patient per-day (marginal) cost MC_{jt}.

Given the collection of private prices $P_{J_t} = \{P_{jt}\}_{j \in J_t}$, and quality vectors $W_{J_t} = \{W_{jt}\}_{j \in J_t}$ new patients allocate across nursing homes. Specifically, for a new patient i, the probability of choosing nursing home j in t is

$$s_{ijt}\left(P_{J_t}, W_{J_t}; J_t\right), \tag{3}$$

and if LOS_i is the patient's length of stay, then average (per-bed) variable profit for nursing home j is

$$\pi_{jt}\left(P_{J_t}, W_{J_t}; J_t\right) = \frac{1}{beds_{jt}} \sum_i s_{ijt}\left(P_{J_t}, W_{J_t}; J_t\right) LOS_i(\overline{R}_{jt} - MC_{jt}). \tag{4}$$

In this expression $\overline{R}_{jt}$ is the average per-diem revenue, which depends on P_{jt} but also on the Medicaid and Medicare reimbursement rates. Because I do not observe the share of i's stay covered by the various payers, I instead assign the facility-year level average of rates across the three primary payers (Medicare, Medicaid, and the private price), weighted by their share of overall days, which I observe at the facility-year level.

After new admissions are determined and firms realize their variable profits π_{jt}, each firm observes a private fixed cost of continuing to the next period, κ_{jt}, which is drawn from the distribution F_κ. Firm j then makes a binary decision whether to exit (and receive zero) or to pay κ_{jt} to continue to period $t+1$. Firms that close may not return, and so exiting is a terminal state.

The game played by nursing homes can therefore be summarized as follows:

1. Firms choose prices P_{J_t} paid by private (i.e., non-Medicaid and non-Medicare) patients.
2. Quality-of-care deficiencies W_{J_t} are realized.
3. New patients arrive, patients allocate, and firms realize variable profits π_{jt}, $j \in J_t$.
4. Each firm receives an independent fixed cost draw from a known distribution F_κ.

11. It is important to note that I do not model the entry decision. Given the very limited entry observed over the sample period (Section 2.1), this assumption likely makes little difference, as the estimated entry costs would be prohibitively high.

5. Firms choose to exit (receive zero) or continue (pay κ_{jt}).
6. Continuing firms move to the next period.

5.2 Demand Parametrization

Nursing home demand is fully static, as in Hackmann (2019). Each period t, a fixed cohort N_t of new patients arrive and select a facility at which to receive nursing home care. Patients vary in their payer status, reflecting that some patients are exposed to private daily prices P_{J_t} at some point in their stay and others, whose stays are fully covered by public insurers, are not. Due to data limitations, I abstract from any cost-sharing borne by public patients, such as any coinsurance paid during the Medicare-funded portion of their stay.

Demand is determined as follows: patient i with payer type $\psi \in \{\text{public}, \text{private}\}$ considering nursing home care chooses among all facilities j open in year t, to maximize her indirect conditional utility:

$$u_{ijt}^{\psi} = \alpha^d \log(Dist_{ij}) + \underbrace{\alpha_{\psi}^{defs} W_{jt} + \alpha^p P_{jt}^{\psi} + \xi_{jt}^{\psi}}_{\delta_{jt}^{\psi}} + \varepsilon_{ijt} \tag{5}$$

where $\log(Dist_{ij})$ is the log-distance between resident i's home zip code centroid and the address of facility j. W_{jt} is the number of quality-of-care deficiency citations per bed in facility j in year t. P_{jt} is the per diem price paid only by private patients. ξ_{jt} captures unobserved (to the econometrician) facility quality. ε_{ijt} is an independent and identically distributed type-1 extreme value taste shock.

Distinguishing between patients of differing payer types is crucial for estimating the price sensitivity parameter α^p. Specifically, I define public patients as those whose stays were fully covered by Medicare (which I observe directly using the Medicare claims[12] linked to the MDS assessments) or those patients who were enrolled in Medicaid for the full duration of their stay.[13] Patients whose stays outlasted the Medicare coverage window and were not enrolled in Medicaid for at least some duration of their stay are assumed to have paid the private daily prices.[14] To compute the consumer surplus changes under the counterfactual policy experiments, I assume that public patients share the private patient marginal utility of income α^p. Additionally, for greater flexibility I allow the terms parameterizing taste for quality α_{ψ}^{defs} as well as unobserved facility quality ξ_{jt}^{ψ} to vary by payer type, anticipating that private and public patients may vary in their sensitivity to quality.

Collecting facility-payer-year specific terms together into δ_{jt}^{ψ}, I can now express the probability that patient i with payer type ψ arriving in year t chooses facility j using the familiar logit choice structure (McFadden 1974; Berry 1994):

$$s_{ijt}\left(P_{J_t}, W_{J_t}; J_t\right) = \frac{\exp\left(\alpha^d \log(Dist_{ij}) + \delta_{jt}^{\psi}\right)}{\sum_{k \in J_t} \exp\left(\alpha^d \log(Dist_{ij}) + \delta_{kt}^{\psi}\right)} \tag{6}$$

12. By necessity, I classify all Medicare Advantage enrollees as public patients, as I do not observe their Medicare claims, and so they do not contribute to estimation of the price elasticity.

13. I observe only monthly Medicaid enrollment, not individual Medicaid claims.

14. Reassuringly, this assignment rule seems to perform well. The price sensitivity parameter I estimate in Section 6 is quite similar to the one recovered by Hackmann (2019), who does observe Medicaid claims.

where J_t contains the set of all within-state operating nursing homes in year t in the state.

5.3 Optimal Exit Decisions

Because demand evolves exogenously each period as new patients arrive, the relevant state space for the exit decision can be summarized by

$$\mathcal{S} = \{s_{ijt} \in [0,1]^{|J_t|} \mid i \in N_t\}. \tag{7}$$

In estimation, this state space will be discretized and approximated, to reduce dimensionality. Section 6 contains details on the approximating state variables. I consider the firm's exit decision at the end of each period, after prices have been determined, and so I abstract away from the optimal pricing decision.

Given the stage timing, the Bellman equation for the value of an active firm can be written as a simple function of $\mathbf{s} \in \mathcal{S}$ and the fixed cost draw κ_{jt}:

$$V(\mathbf{s}; \kappa_{jt}) = \pi_{jt} + \max\left\{\beta EV(\mathbf{s}) - \kappa_{jt}, 0\right\} \tag{8}$$

where π_{jt} is the stage variable profit earned by firm j given $\mathbf{s}$, $EV(\mathbf{s})$ is the continuation value from staying and $0 < \beta < 1$ is the discount rate. This implies the simple decision rule that firms exit if $\kappa_{jt} > \beta EV(\mathbf{s})$, or if the costs of staying outweigh the discounted expected benefits of doing so.

With the known distribution of fixed costs F_κ, the probability that firm j exits given $\mathbf{s} \in \mathcal{S}$ can be expressed as:

$$\Pr(exit_{jt}|\mathbf{s}) = 1 - F_\kappa\big(\beta EV(\mathbf{s})\big). \tag{9}$$

Letting $(\mathbf{s}', \kappa')$ denote next-period variables, omitting subscripts for simplicity, and—with a slight abuse of notation—$\pi(\mathbf{s})$ the variable profit in state $\mathbf{s}$, the continuation value $EV(\mathbf{s})$ can be written as:

$$\begin{aligned} EV(\mathbf{s}) &= \mathbb{E}_{\mathbf{s}'}\Big[\pi(\mathbf{s}') + \mathbb{E}_{\kappa'}\big[\max\left\{\beta EV(\mathbf{s}') - \kappa', 0\right\}\big]\Big] \\ &= \mathbb{E}_{\mathbf{s}'}\Big[\pi(\mathbf{s}') + F_\kappa(\beta EV(\mathbf{s}'))\big[\beta EV(\mathbf{s}') - \mathbb{E}_{\kappa'}(\kappa'|\kappa' \leq \beta EV(\mathbf{s}'))\big]\Big]. \end{aligned} \tag{10}$$

I assume that κ_{jt} follows an exponential distribution with rate parameter $1/\kappa$ and so equation (10) simplifies to the following convenient form:[15]

$$EV(\mathbf{s}) = \mathbb{E}_{\mathbf{s}'}\Big[\pi(\mathbf{s}') + \beta EV(\mathbf{s}') - \kappa F_\kappa(\beta EV(\mathbf{s}'))\Big]. \tag{11}$$

Equation (11) illustrates the straightforward interpretation of the continuation values, as the sum

15. The assumption that fixed costs are exponentially distributed is not crucial, though it does appear to fit the data well (Section 6), and enables the matrix inversion used to estimate the continuation values EV, speeding up estimation.

of expected stage profits and the future continuation value, less the expected cost of continuing. After discretizing the state space and specifying a transition matrix, equation (11) can be solved for the continuation values using the nested fixed point approach. However, to speed up estimation, Pakes, Ostrovsky, and Berry (2007) point out one can avoid solving the fixed point for each guess of the parameter κ by instead using a matrix inversion approach. I detail this procedure in Section 6.

6 Model Estimation

6.1 Observables and Estimation Overview

Estimation proceeds sequentially, following the stage timing outlined in Section 5.1. The demand- and supply-sides of the model are estimated separately, with the demand estimates used as inputs in the dynamic supply estimation. The estimation procedure spans several datasets and sets of years, and I summarize each of the data sources used in Appendix Table C.1.

The demand-side of the model is estimated using micro choice data from new nursing home admissions, which I construct using admission assessments from the MDS. Due to data access, I restrict my attention to only Illinois nursing home admissions spanning 2012-2017, as I observe facility-year level Medicaid and private daily rates using state cost reports from this period. In addition to data availability, Illinois is a particularly appealing venue for studying the impacts of counterfactual reimbursement policies on nursing home exits. The state saw the fourth most closures over my sample period (following California, Texas, and Ohio), which providers have alleged is owed to the state's low Medicaid rate. Indeed, a group of providers sued the state in 2018 – following the end of my sample period – claiming the low reimbursement rates will cause them to shutdown, thereby limiting access for Medicaid patients (Rucinski 2018).

While Illinois has witnessed a high rate of nursing home exits, there are still too few closures in the state during my sample window ($N = 18$ from 2012 to 2017) to provide consistent estimates of the exit cost parameter κ. For this reason, I make use of my full national sample of exits to estimate the supply-side of the model. As I do not have demand estimates for nursing homes outside of Illinois (or those in Illinois beyond the 2012-2017 window), I must rely on a reduced form profit function and an approximation to the model state space. Specifically, I approximate the state space (the demand vector s, which is unobserved for most firms) with a pair of annual state variables z: each facility's occupancy rate and share of Medicaid patients, both of which I observe nationally. These variables capture two key dimensions of demand, and are strongly predictive of variable profits (Figure 2). To accommodate the endogeneity concern that facilities in areas with low occupancy or high Medicaid shares operate in areas that are otherwise unprofitable, I supplement the reduced form profit function with county-level fixed effects.

To construct the reduced form profit function, I rely on the nationally available Medicare cost reports to construct firm-year level measures of revenues and variable costs from 2011-2019.[16] Recall

16. The accounting measures in these data are notoriously unreliable prior to 2011. While a longer panel is available

the aim of the model is to estimate the fixed cost parameter κ, and the payoffs in each state are variable profits. In principle, because the cost data contain measures of accounting fixed costs, I could estimate the fixed cost parameter directly. However, there are substantial limitations to this simpler approach, related to the distinction between accounting and economic profits. The fixed costs reported in the data are not necessarily the same as the model-relevant fixed costs, and there are further known issues with the accounting of fixed costs in this setting. Specifically, many nursing home owners legally separate their firms into property management and operating companies, with the aim of masking profits as rental payments (Harrington et al. 2021). As a result, while variable costs (primarily, direct care labor) are well-measured, the accounting fixed costs are frequently inaccurately reported.

Thus, I relate the firm's reported variable profits to the observed state variables (occupancy and Medicaid shares) using a reduced form profit function. To augment estimation, I supplement this reduced form profit function with the micro moments implied by equation (4), incorporating the demand estimates for the Illinois sample. This profit function is then sufficient to estimate the fixed cost parameter κ, using the observed exit rates in each state.

There is a key limitation to this approach to estimating the supply side. Specifically, given the state space approximation, I ignore the oligopoly game played between firms. There are both data availability and computational restrictions for this. Even if one were to observe the true states (i.e., demand vector s for all firm-years), the dimensionality of the state space is prohibitively large: given by 2^N, where N is the number of active firms. In Illinois, $N = 634$, making computing the continuation values for each point in the state space impossible. A consequence is that I will be restricted to only myopic single-agent counterfactuals when I consider alternative reimbursement schemes, rather than simulating equilibrium outcomes.

Next, I provide more detail on the estimation procedure, beginning with the demand-side of the model. Interested readers can skip to Section 6.4 for the estimation results.

6.2 Demand Estimation

In the model, firms take demand as given and so I begin by estimating the demand-side of the model. I employ a two-step procedure which follows Hackmann (2019).

Step One: I estimate preferences over distance, α^d, and the payer-specific mean utilities δ^{ψ}_{jt}. For identification, one mean utility per year is normalized to zero. This step is estimated via maximum likelihood, relying on the individual choice data and the logit choice probabilities in equation (6).

Step Two: In the model, firms observe ξ^{ψ}_{jt} before choosing prices P_{jt}. Thus, prices are endogenously determined, and so I require instruments to recover the price coefficient α^p. Given the rich cost data available, I use the average costs (per patient-day) of nearby competitors to estimate the taste parameter on private per diem price. The logic of such instruments, standard in industrial organization, is that costs affect prices, but do not directly enter the utility function given by equation (5). I estimate α^{defs}_{ψ} and α^p using two-stage least squares, and recover ξ^{ψ}_{jt} as the residuals.

after 2019, a large idiosyncratic shock hit the industry in 2020.

6.3 Supply Estimation

Supply estimation proceeds in three steps. In the first step, I construct and discretize an approximate state space to the demand vector s, which has low enough dimensionality to resolve the computational burden, in addition to providing states for the firms lacking demand estimates. I also compute the transition probability matrix using the observed frequencies in the data. In the second step, I relate the observed approximating state variables (Medicaid share and occupancy rate) to variable profits using a reduced form profit function. Because I supplement this estimation with the demand moments from equation (4), I estimate the reduced form profit using the generalized method of moments. In the final step, I use the profit parameters to estimate the fixed cost parameter κ, using the method of moments approach introduced by Pakes, Ostrovsky, and Berry (2007).

Step One: The state variables I use to approximate the demand vector s_{jt} are the occupancy rate occ_{jt} and the share of Medicaid patients $mcaid_{jt}$ of firm j in year t. I discretize each of these terms into 6 equally sized bins. To accommodate the concern that areas with more Medicaid shares may be unobservably less profitable, I estimate a regression of firm-year average variable profits on the resulting $(occ_{jt}, mcaid_{jt})$ pairs and a set of county fixed effects. However, including each of these fixed effects would explode the state space again, and so I follow Dunne et al. (2013) and group the fixed effects into 4 equally sized bins. This substantially reduces the computational requirements, while the estimated fit remains quite high: the R^2 moves from 0.532 to 0.512 when moving from a full fixed effects approach to the binned fixed effects. The state variables are then denoted by the triple $z_{jt} = (occ_{jt}, mcaid_{jt}, \overline{county}_{jt})$, where $\overline{county}_{jt}$ is the county fixed effect bin. The resulting state space is then of length $6 \times 6 \times 4 = 144$.

I impose an additional assumption that the state variables z_{jt} evolve according to a Markovian transition matrix F_z. To calculate the empirical transition probabilities, I exploit the fact that while some state variables evolve, the county fixed effects do not change over time. Hence, I can write $F(occ', mcaid', \overline{county}|occ, mcaid, \overline{county}) = F(occ', mcaid'|occ, mcaid) \cdot I_{\overline{county}}$, and estimate each smaller matrix using their observed frequencies in the data.

Step Two: I estimate a nonlinear profit function $g(\cdot)$ containing a coefficient θ for each point in the state space, using a GMM estimator aided by two sets of moments. First, I use only 'macro' moments, which relate the state variables z_{jt} to the accounting variable profits π_{jt}^{macro}. Second, I supplement the macro moments with 'micro' moments coming from only the Illinois facilities with demand estimates. The micro-moments relate the model-implied profits $\hat{\pi}_{jt}^{micro}$ with the state variables z_{jt}. For the policy exercises in Section 7 I will need to compute the state variables z_{jt} under counterfactual allocations using the micro-data, and so for completeness I also include an additional set of moments, which equate the model-implied state variables $\hat{z}_{jt}^{micro}$ with the model-

implied profits $\hat{\pi}_{jt}^{micro}$. Hence, these moments then include:

$$\mathbb{E}\big[\pi_{jt}^{macro} - g(z_{jt};\theta)\big] = 0$$
$$\mathbb{E}\big[\pi_{jt}^{macro} - g(\hat{z}_{jt}^{micro};\theta)\big] = 0$$
$$\mathbb{E}\big[\hat{\pi}_{jt}^{micro} + \psi - g(z_{jt}^{micro};\theta)\big] = 0$$

where I include an additional intercept ψ in the final set of micro moments to account for any level differences in the reported profits and the model-implied profits. Denoting the corresponding sample analogues G_1^{macro}, G_2^{macro}, and G_3^{micro}, I stack these moments and refer to the stacked row vector as:

$$G(\theta) = \Big[G_1^{macro}, G_2^{macro}, G_3^{micro}\Big]$$

The GMM estimator is then given by:

$$\hat{\theta}^{GMM} = \underset{\theta}{\operatorname{argmin}}\, G(\theta) W G(\theta)'$$

where W is a diagonal weighting matrix. I use the two-step efficient GMM estimator (Hansen 1982) of θ from the stacked moments. See Appendix A.1 for more details on this procedure.

Step Three: With the profit function in hand, I can compute the continuation values EV evaluated at each point in the state space for a given value of κ. While equation (11) is contraction mapping, and therefore relatively easy to solve using the nested fixed point algorithm for each guess of the parameter κ, Pakes, Ostrovsky, and Berry (2007) point out that one can side-step solving the fixed point for each guess of the parameters by iterating forward the value of EV infinitely many periods. Performing this forward iteration and replacing the states s with their approximations z, equation (11) can be rewritten in matrix form as:

$$EV = \big[I - \beta F_z\big]^{-1} F_z \big[\pi - \kappa(1 - \Pr(exit))\big] \tag{12}$$

where I is the identity matrix and $\Pr(exit)$ contains the exit probabilities in each state. Hence, the continuation values can be easily computed using consistent estimates of the transition and exit probabilities, in addition to the stage profits π in each state. I assume a discount factor of $\beta = 0.9$. The nonlinear function estimated in the second step provides a consistent estimate of π in each state, and I use the empirical exit rates to compute $\Pr(exit)$ in each state. I can therefore estimate the exit cost parameter κ using the moments suggested by equation (9). Specifically, I match the observed exit rates in each state with those implied by the model.[17]

17. I can also estimate the model using maximum likelihood, but Pakes, Ostrovsky, and Berry (2007) note that the method of moments is preferable when exit rates are very small, as the estimates are more robust to noise in the continuation values.

6.4 Model Estimates

Table 4 presents summary statistics on the annual facility panel used to estimate the dynamic component of the model. Firms report about $36,000 per bed in variable profits, though firms that exit tend to report significantly lower profits (about $26,000 across years), and particularly so in their last year prior to exit (falling to $22,000). Similarly, exiting firms report lower occupancy rates (70% vs 81%) and higher shares of Medicaid patients (69% vs 64%) at a given point in time, consistent with the preliminary patterns shown in Figure 2.

	All	Stayers	Exiters	
			All Years	Exit Year
	(1)	(2)	(3)	(4)
Income (per-bed)	83.93	84.34	65.65	59.71
Variable Profit (per-bed)	36.09	36.31	26.23	22.29
Accounting Fixed Cost (per-bed)	26.64	26.73	22.28	21.38
Share Medicaid (%)	63.56	63.44	68.69	70.27
Occupancy (%)	80.86	81.10	70.08	63.74
Pr(Exit)	0.005	0.000	0.221	1.000
Observations	105,125	102,835	2,290	506
Firms	13,172	12,666	506	506

Table 4: Facility Panel Summary Statistics

Notes: Table reports sample statistics on the facility panel used to estimate the supply side of the model as described in Section 6. All financial terms are denominated in 2017 dollars, and expressed in thousands.

Figure 8 presents the joint distribution of the continuation values EV and the fitted stage variable profits. Each circle corresponds to a point in the state space and is weighted by the number of facility-years observed in each state. Unsurprisingly, the two are strongly positively correlated: firms that have higher stage profits also have higher continuation values. To illustrate the role of the state variables, I highlight the states corresponding to the top sextile of occupancy and Medicaid shares. Firms with higher shares of Medicaid patients have both the lowest stage profits as well as smaller continuation values; the converse is true for occupancy rates. This reflects that there is significant inertia in the transition matrix, and that firms do not observe signficant swings in their patient census across years, either in magnitude or makeup. Further statistics on the GMM estimates of θ and the continuation values EV are reported in Appendix Tables C.3 and C.4, respectively.

The demand and fixed cost estimates are reported in Table 5. The results imply that private patients have a much stronger taste for quality: these patients exhibit a willingness to pay of $11.2 to move down one standard deviation in the deficiencies measure whereas public patients value the same improvement at only $3.0 per day. However, I find that the taste for distance strongly dwarfs both groups' taste for quality. The demand results suggest that patients would be willing

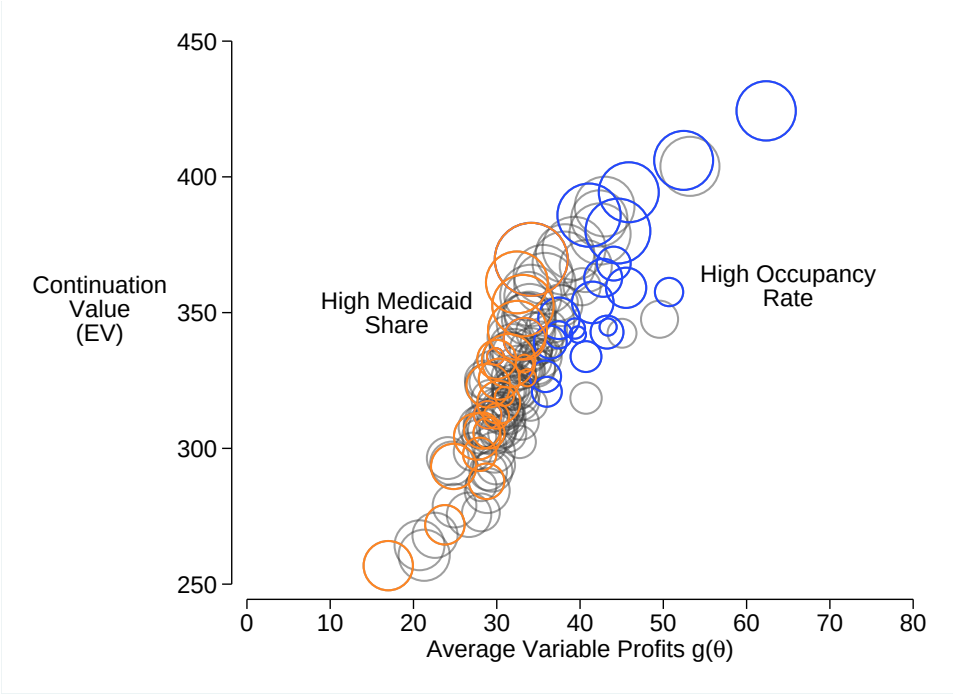


Figure 8: Joint Distribution of Continuation Value and Stage Profits

Notes: Figure presents supply side estimation results detailed in Section 6. Each circle represents a point in the state space z_{jt}, weighted by the number of facility-years observed at each state. The results demonstrate the positive covariance between the fitted stage profits $g(\theta)$ and the corresponding continuation value EV for each state. States corresponding to the top sextiles of occupancy (corresponding to more profitable facilities) are shaded in blue, whereas states corresponding to the top sextiles of Medicaid shares are shaded in orange.

to pay an additional \$73.50 per day to avoid a 10 kilometer increase in distance from the median. These results, consistent with prior work on estimating nursing home demand, likely combine a variety of factors: the importance of distance for family visitation, behavioral mistakes on the part of patients, their children's preferences over travel time, and so on. For the purposes of estimating the dynamic supply model (and conducting the counterfactuals), these caveats are unimportant, as the only requirement is that the demand-side parameters fit the choice data well.

The bottom panel of Table 5 presents estimates of the fixed cost parameter κ, estimated both with and without the use of the micro-moments generated from the demand system.[18] Incorporating the micro-moments to aid in estimation produces a slightly higher estimate of the fixed cost parameter κ, which may be driven by regional differences unique to Illinois, where the micro-moments are defined. I find plausible estimates of the fixed cost term: a representative firm receiving a draw from the 50th percentile of F_κ (about \$38,000) would receive approximately zero economic profit, given their variable profits (\$36,000) reported in Table 4. This plausible estimate of the fixed cost

18. In the former case, the GMM estimator corresponds to the just-identified case, and so $g(\theta)$ is equivalent to an ordinary least squares regression of accounting variable profits on the state vector z_{jt}.

Variable	Parameter	Estimate		Mean	SD
log(Distance)	α^d	-1.746 (0.001)		14.7	27.1
		Public	Private		
Deficiencies	α^{defs}	-1.131 (0.515)	-4.254 (0.782)	0.057	0.050
Price	α^p	—	-0.019 (0.003)	213.6	85.8
Patients	N	609,001			
Fixed Cost	κ	41.770	54.746		
Including Micro-Moments		No	Yes		

Table 5: Demand and Supply Estimates

Notes: Table reports estimates from the demand system and estimates of the unobserved fixed cost parameter. The distance summary statistics (mean and SD) are reported in kilometers. Deficiencies are measured per bed. The price and fixed cost parameters correspond to 2017 dollars. The fixed cost parameter is expressed in thousands.

parameter reassures that the model fits the data well.

7 Counterfactual Reimbursement Policies

7.1 Simulations

Recall the aim of the model is to examine how nursing home exits would respond to alternative reimbursement policies. With the estimates in hand, I now simulate the evolution of the Illinois nursing home market over the period 2012-2017. As a benchmark, I begin by examining the baseline scenario, or the model's prediction of facility exits under the current reimbursement system.

Turning next to counterfactuals, I examine the impacts of alternative reimbursement policies which adjust the Medicaid rate for various sets of firms. The low Medicaid per diem rate is often cited as a culprit for the current wave of closures (see Section 2.1), and so this is a natural policy lever to consider adjusting. I start by examining the impacts of a universal 10% increase in the daily Medicaid rate. Such a policy would raise profits for all firms in the state, and particularly so for those with a high share of Medicaid residents. However, given the survival gains documented in Section 4, the desirability of such a policy is not ex ante obvious. In particular, such a policy may avert closures that would have generated survival-improving reallocations.

As such, given the significant mortality effect heterogeneity by local market conditions highlighted in Section 4, I consider a second set of more narrowly targeted policies which would raise rates for only certain firms. Such programs are similar in spirit to the Rural Hospital Flexibility program, which provides higher Medicare rates to financially vulnerable 'Critical Access Hospitals'

in rural areas, with the aim of sustaining access to healthcare services. There is currently no such existing program for nursing homes. In addition to targeting firms by their market concentration, I also examine more common targeting measures, such as targeting firms operating in low-income zip codes (those operating in the bottom quartile of median household income) as well as those in rural counties.

To evaluate the mortality impacts of the exits induced under each policy, I compute the implied changes in life expectancy for residents of facilities induced to exit under each scenario. To do so, I rely on the mortality effects estimated in Section 4, coupled with predicted mortality hazards using the demographic and health measures available in the MDS. To translate the life expectancy effects into dollar terms, I apply the Department of Transportation's 2017 value of statistical life of \$10.2m,[19] which I convert to monthly terms using U.S. life expectancy, or approximately \$11,000 per month. Appendix B provides further details on computing these life expectancy effects, as well as additional details on the simulation procedure.

In addition to calculating the life expectancy cost, I also compute the change in consumer surplus, which may be interpreted as the consumer valuation of access to care. This calculation should be interpreted with significant caveats. For instance, it may be difficult to take the patients' revealed preferences at face value, as their decisions may reflect imperfect information over quality, the preferences of their agents (children), endogenous location decisions of facilities and patients, and so on. Nonetheless, using the derivation in McFadden (1981), the unconditional compensating variation can be calculated as:

$$\Delta CS = \frac{1}{\alpha^p}\Bigg[\sum_i \log\Bigg(\sum_{j\in J^1}\exp(\alpha^d \log(Dist_{ij}) + \alpha_\psi^{defs} Defs_{jt})\Bigg) LOS_i \\ - \sum_i \log\Bigg(\sum_{j\in J^0}\exp(\alpha^d \log(Dist_{ij}) + \alpha_\psi^{defs} Defs_{jt})\Bigg) LOS_i\Bigg]$$

where J^1 is the set of open firms under the reference scenario, and J^0 is the complete set of firms. I compute the change in consumer surplus driven only by distance and quality, as I do not model the firm's price-setting decision. Individuals are weighted by their length of stay.

7.2 Results

The aggregate effects under each scenario are summarized in Table 6. The baseline model, presented in column (1), appears to fit the data well, predicting 19 exits over the period 2012-2017, compared to 18 realized exits that occurred over this period. The net effect of these exits on resident life expectancy is positive (as indicated by the reduced form mortality results of Section 4), generating additional longevity valued at around \$10 million. However, these exits also generate a \$124 million loss in consumer surplus from changes in the patients' choice sets.

The universal rate increase, column (2), abates 4 of these closures. These additional averted

19. https://www.transportation.gov/office-policy/transportation-policy/revised-departmental-guidance-on-valuation-of-a-statistical-life-in-economic-analysis

	Baseline	Universal Increase	Targeted Subsidy		
			Concentration	Income	Rurality
	(1)	(2)	(3)	(4)	(5)
Number of Exits	19	15	16	18	15
Δ Life Expectancy					
Months Gained	2,924	2,433	2,957	2,696	2,510
Months Lost	-2,003	-1,539	-845	-1,965	-1,505
Δ VSL ($ mil)	9.96	9.67	22.84	7.91	10.87
Δ Consumer Surplus ($ mil)	-124.04	-103.35	-106.00	-119.48	-104.41
Δ G ($ mil)	0.00	513.27	148.85	239.02	183.49

Table 6: Counterfactuals

Notes: Table summarizes the results of the counterfactual reimbursement policy simulations in the Illinois nursing home industry from 2012-2017, relative to no exits. The changes in life expectancy are determined using the residents of facilities predicted to exit under each scenario, assuming a Weibull survival model. The value of statistical life (VSL) used is $10.1m, and is expressed in months using the U.S. life expectancy from 2017. The change in consumer surplus is determined using only changes in observed utility stemming from distance and deficiencies per bed. The change in government spending is computed as the additional cost of the subsidy multiplied by the number of Medicaid days. Column (1) presents the results from the baseline model. Column (2) presents the results from the universal 10% Medicaid reimbursement rate increase. The remaining columns presents results from the targeted subsidies. Column (3) corresponds to a subsidy targeting concentrated nursing homes. Column (4) contains results from the subsidy targeting firms in low-income zip codes. Column (5) contains results from the subsidy targeting all firms in rural counties. All financial terms are denominated in 2017 dollars and expressed in thousands.

closures restrict both the life expectancy gains and losses, generating a smaller but comparable change in VSL as under the baseline scenario. However, by reducing closures the consumer welfare loss falls to only $103 million. In contrast, the concentration-based targeted subsidy, column (3), permits one more exit (16 over the sample window) than the universal rate increase, though the composition of exiting firms varies. This targeted subsidy generates the highest life expectancy gains, valued at about $22 million, with a comparable consumer surplus loss as under the universal rate increase. Targeting on median household income or county rurality, columns (4) and (5), generate much worse outcomes than targeting on concentration. The VSL improvements are much smaller, reflecting that many of these additional dollars go to facilities that are either inframarginal over exiting, in the case of the income-based subsidy, or operating with nearby competitors to absorb the excess demand, in the case of the rural subsidy.

These aggregate impacts of each scenario mask significant heterogeneity in the life expectancy effects across individuals. To this end, I also examine the distribution of life expectancy impacts under each scenario, presented in Figure 9. As the net effect on life expectancy of exits is positive, the bulk of the distribution always falls to the right of zero. In the baseline scenario, there is a mass of people whose lives are extended by at least 12 months due to the reallocative benefits

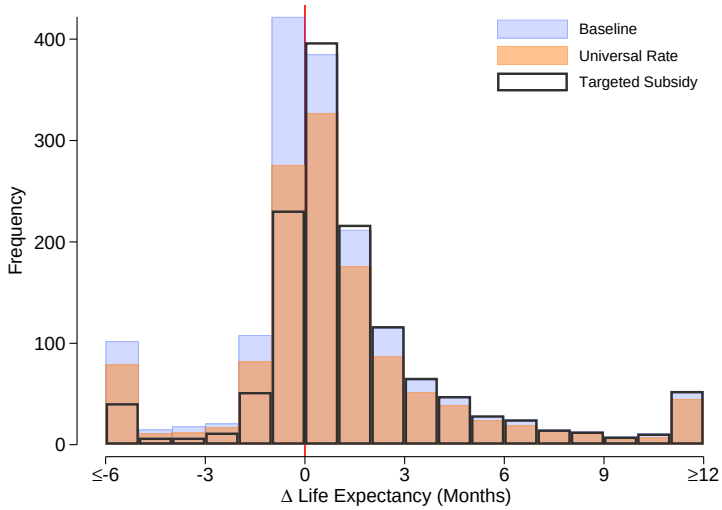


Figure 9: Distributional Impacts of Reimbursement Policies on Life Expectancy

Notes: Figure presents the results of the alternative reimbursement policy experiments, plotting the distribution of the effects of each policy on life expectancy, relying on the mortality effects estimated in Section 4. The targeted subsidy preserves the gains in life expectancy expected from the baseline exit rate.

of the closures (the model predicts 2,924 months of life gained). Importantly, though, there is a significant mass with life expectancy effects below zero: these are residents whose lives are cut short by at least one month, due to the short-run mortality costs of the closures (in aggregate, 2,003 months of life lost). As the universal rate increase reduces the number of closures, there are fewer residents affected, but the distribution of life expectancy effects is similar to baseline. The targeted subsidy, on the other hand, aims to preserve the life expectancy gains, while minimizing the losses. Indeed, the targeted subsidy slightly increases the number of months gained (2,957) and substantially limits the months lost (845). It does so by allowing the efficient closures in competitive markets to continue, generating a distribution of life expectancy effects that is more favorable.

These exercises hint at a tradeoff between the survival benefits of efficient closures and the consumer welfare losses from changes in the choice set. While the universal Medicaid rate increase averts more closures than under the targeted subsidy, it also diminishes the life expectancy gains. To explore this access-quality tradeoff, I consider the effects of a broader set of flexible rate increases given by the following expression:

$$r_{jt} = m\mathbb{1}[j \in J_t^m] + c\mathbb{1}[j \in J_t^c]$$

where J_t^m and J_t^c denote the sets of firms operating in competitive and concentrated, respectively. r_{jt} is the percent increase in the Medicaid rate, and so one can denote the subsidized Medicaid rate as $\tilde{R}_{jt}^{mcaid} = (1 + r_{jt})R_{jt}^{mcaid}$. These (m, c) pairs generalize the earlier interventions, i.e. the universal rate increase corresponds to $(0.1, 0.1)$ whereas the concentration-based targeting subsidy

is $(0, 0.2)$. I compute the aggregate life expectancy impacts, consumer surplus loss, and cost for each $(m, c) \in [0, 0.2]^2$, in 0.02 increments.

These results are summarized in Figure 10, where each cell corresponds to an (m, c) pair. The tables illustrate the trade-off between quality and access under the different subsidy designs. Panel (a) shows the policy which maximizes resident life-expectancy is the one which most aggressively subsidizes firms in concentrated markets, $c = 0.2$, with no subsidy for firms in competitive markets, $m = 0$. Such a policy would preserve all the reallocative life expectancy gains from allowing firms in competitive markets to close, while averting the losses from exits in concentrated markets. Because there are many fewer firms in concentrated markets, this policy is also significantly cheaper than a universal rate increase, as panel (c) indicates. Panel (b) illustrates that the consumer surplus maximizing policy is, naturally, one that generates the fewest losses in the patients' choice sets, and so corresponds to aggressively subsidizing all firms. That is, a high universal rate increase $(0.2, 0.2)$ generates the smallest welfare loss by minimizing the total number of exits, while also being the costliest policy to implement. The divergence between panels (a) and (b) reflects that patients' revealed preferences indicate a low valuation of quality, and a high valuation on access, via distance.

There are several important caveats to these exercises. The first, as noted earlier, is that the consumer surplus calculations require strict interpretations of the demand parameters estimated in Section 6 as reflecting patients' true preferences. This assumption may not hold if, for instance, other agents (such as the patients' children) are involved in the nursing home decision, facilities endogenously locate near patients with taste shocks, or patients are not fully informed about the quality of the nursing homes. Unobserved restrictions on patients choice sets, such as through selective admissions practices (Gandhi 2020), may also distort the parameter estimates away from their true values. Moreover, there are known limitations to the substitution patterns generated by standard logit models (Berry, Levinsohn, and Pakes 1995), which may also generate biased changes in welfare from adding or removing items from consumers' choice sets (Ackerberg and Rysman 2005).

Second, I do not fully solve the dynamic game played between firms in each of the counterfactual scenarios, and so impose the additional assumption that firms operate as myopic single agents. I require that firms do not respond to (for instance) changes in the transition matrices induced by other firms' exits following the policy changes. While this greatly simplifies computation, doing so may fail to capture realistic responses by firms. Recent innovations in approximate methods for solving dynamic oligopoly games provide potential avenues to enrich these counterfactuals to incorporate more realistic firm behaviors (Ifrach and Weintraub 2017; Gowrisankaran, Langer, and Zhang 2022).

Third, the model and counterfactual simulations hold fixed facility characteristics (in particular the quality of care deficiencies W_{jt}), and therefore do not capture any endogenous quality responses to payment reforms. Firms may respond to higher reimbursement rates by investing in quality-improving technologies so as to attract more patients. In this case, the counterfactual simulations

Competitive Subsidy \ Concentrated Subsidy	0%	2%	4%	6%	8%	10%	12%	14%	16%	18%	20%
0%	921.2	921.2	921.2	1302.1	1302.1	1381.3	1381.3	1381.3	2041.3	2111.8	2111.8
2%	921.2	921.2	921.2	1302.1	1302.1	1381.3	1381.3	1381.3	2041.3	2111.8	2111.8
4%	694.8	694.8	694.8	1075.7	1075.7	1154.9	1154.9	1154.9	1814.9	1885.4	1885.4
6%	694.8	694.8	694.8	1075.7	1075.7	1154.9	1154.9	1154.9	1814.9	1885.4	1885.4
8%	433.4	433.4	433.4	814.3	814.3	893.4	893.4	893.4	1553.5	1624.0	1624.0
10%	433.4	433.4	433.4	814.3	814.3	893.4	893.4	893.4	1553.5	1624.0	1624.0
12%	433.4	433.4	433.4	814.3	814.3	893.4	893.4	893.4	1553.5	1624.0	1624.0
14%	433.4	433.4	433.4	814.3	814.3	893.4	893.4	893.4	1553.5	1624.0	1624.0
16%	247.5	247.5	247.5	628.5	628.5	707.6	707.6	707.6	1367.6	1438.1	1438.1
18%	247.5	247.5	247.5	628.5	628.5	707.6	707.6	707.6	1367.6	1438.1	1438.1
20%	247.5	247.5	247.5	628.5	628.5	707.6	707.6	707.6	1367.6	1438.1	1438.1

(a) Changes in Total Life Expectancy (Months)

Competitive Subsidy \ Concentrated Subsidy	0%	2%	4%	6%	8%	10%	12%	14%	16%	18%	20%
0%	-124.0	-124.0	-124.0	-118.3	-118.3	-112.5	-112.5	-112.5	-106.0	-106.0	-106.0
2%	-124.0	-124.0	-124.0	-118.3	-118.3	-112.5	-112.5	-112.5	-106.0	-106.0	-106.0
4%	-119.4	-119.4	-119.4	-113.7	-113.7	-107.9	-107.9	-107.9	-101.4	-101.4	-101.4
6%	-119.4	-119.4	-119.4	-113.7	-113.7	-107.9	-107.9	-107.9	-101.4	-101.4	-101.4
8%	-114.9	-114.9	-114.9	-109.2	-109.2	-103.4	-103.4	-103.4	-96.9	-96.9	-96.9
10%	-114.9	-114.9	-114.9	-109.2	-109.2	-103.4	-103.4	-103.4	-96.9	-96.9	-96.9
12%	-114.9	-114.9	-114.9	-109.2	-109.2	-103.4	-103.4	-103.4	-96.9	-96.9	-96.9
14%	-114.9	-114.9	-114.9	-109.2	-109.2	-103.4	-103.4	-103.4	-96.9	-96.9	-96.9
16%	-111.3	-111.3	-111.3	-105.6	-105.6	-99.8	-99.8	-99.8	-93.4	-93.4	-93.4
18%	-111.3	-111.3	-111.3	-105.6	-105.6	-99.8	-99.8	-99.8	-93.4	-93.4	-93.4
20%	-111.3	-111.3	-111.3	-105.6	-105.6	-99.8	-99.8	-99.8	-93.4	-93.4	-93.4

(b) Consumer Surplus Loss ($ millions)

Competitive Subsidy \ Concentrated Subsidy	0%	2%	4%	6%	8%	10%	12%	14%	16%	18%	20%
0%	0.0	14.8	29.7	44.5	59.3	74.4	89.3	104.1	119.0	134.0	148.9
2%	87.8	102.6	117.5	132.3	147.1	162.2	177.0	191.9	206.8	221.7	236.6
4%	175.6	190.4	205.3	220.1	234.9	249.9	264.8	279.7	294.5	309.5	324.4
6%	263.4	278.2	293.1	307.9	322.7	337.7	352.6	367.4	382.3	397.2	412.1
8%	351.3	366.1	381.0	395.8	410.6	425.5	440.3	455.2	470.0	484.9	499.8
10%	439.2	454.0	468.8	483.6	498.4	513.3	528.1	543.0	557.8	572.7	587.6
12%	527.0	541.8	556.6	571.4	586.2	601.1	615.9	630.8	645.6	660.5	675.4
14%	614.8	629.7	644.5	659.3	674.1	688.9	703.7	718.6	733.4	748.3	763.2
16%	702.9	717.7	732.5	747.3	762.1	776.8	791.6	806.5	821.3	836.2	851.0
18%	790.8	805.6	820.4	835.1	849.9	864.6	879.5	894.3	909.1	924.0	938.8
20%	878.7	893.4	908.2	923.0	937.8	952.5	967.3	982.1	997.0	1011.8	1026.7

(c) Total Costs ($ millions)

Figure 10: Optimal Subsidy Targeting

Notes: Tables present the results of the optimal subsidy targeting exercise. The horizontal axes correspond to the increase in the Medicaid reimbursement rate for firms in concentrated markets (c) and the vertical axes correspond to the increase in the Medicaid reimbursement rate for firms in competitive markets (m). Figures present the aggregate change in life expectancy, consumer surplus loss, and total cost of each subsidy targeting scheme.

may be significantly understating the welfare gains, both through the consumer valuation of quality in addition to improvements in mortality outcomes at inframarginal firms.

It is worth emphasizing that the costs of each of the policies explored here substantially outweigh their life expectancy and consumer surplus effects, and so these counterfactuals would fail a standard cost-benefit analysis. The size of these interventions reflect the considerable magnitude of public investment in long-term care, and one would require values of statistical life well above their conventional levels to overturn the cost-benefit conclusions on their own. However, as noted, because the model holds quality constant, it is likely that these simulations understate the benefits from raising reimbursement rates.

8 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 transition 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 significantly higher quality, and this reallocation generates significant 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.

I also find important heterogeneity, as the survival gains accrue only to residents in competitive nursing home markets. In contrast, residents in areas with few other nursing homes at the time of exit experience no mortality improvement, but instead face only the sharp initial mortality increases. These results are consistent with widespread media reports about diminishing rural nursing home access, and the tremendous toll such exits impose on residents and their families (Healy 2019; Saslow 2019).

Motivated by these reduced form results, I estimate a dynamic structural model of the nursing home exit decision. I then use the model to examine the effects of counterfactual policies meant to avert closures in these most vulnerable areas with the remaining providers. I find that a universal 10% increase in the Medicaid rate decreases the frequency of nursing home closures, but has the consequence that some low-quality providers remain open in competitive areas. In contrast, a targeted subsidy for facilities in areas with limited access to care improves overall mortality by averting the costliest nursing home closures. Overall, these results suggest that nursing home exits appear to generate positive reallocation, but only under certain conditions. In particular, the benefits are realized only when there are sufficient alternatives for nursing home care.

References

Ackerberg, Daniel A., and Marc Rysman. 2005. "Unobserved Product Differentiation in Discrete-Choice Models: Estimating Price Elasticities and Welfare Effects." *The RAND Journal of Economics* 36 (4): 771–788.

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," 75.

Berry, Steven, James Levinsohn, and Ariel Pakes. 1995. "Automobile Prices in Market Equilibrium." *Econometrica* 63 (4): 841–890.

Berry, Steven T. 1994. "Estimating Discrete-Choice Models of Product Differentiation." *The RAND Journal of Economics* 25 (2): 242–262.

Carroll, Caitlin. 2019. "Impeding Access or Promoting Efficiency? Effects of Rural Hospital Closure on the Cost and Quality of Care," 55.

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, no. 8 (August): 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, January.

Deryugina, Tatyana, and David Molitor. 2020. "Does When You Die Depend on Where You Live? Evidence from Hurricane Katrina." *American Economic Review* 110, no. 11 (November): 3602–3633.

Dunne, Timothy, Shawn D. Klimek, Mark J. Roberts, and Daniel Yi Xu. 2013. "Entry, Exit, and the Determinants of Market Structure." *The RAND Journal of Economics* 44 (3): 462–487.

Einav, Liran, Amy Finkelstein, and Neale Mahoney. 2022. "Producing Health: Measuring Value Added of Nursing Homes," 79.

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, no. 4 (November): 748–758.

Foster, Lucia, John Haltiwanger, and Chad Syverson. 2008. "Reallocation, Firm Turnover, and Efficiency: Selection on Productivity or Profitability?" *American Economic Review* 98, no. 1 (March): 394–425.

Gandhi, Ashvin. 2020. *Picking Your Patients: Selective Admissions in the Nursing Home Industry.* SSRN Scholarly Paper ID 3613950. Rochester, NY: Social Science Research Network, May.

Gandhi, Ashvin, YoungJun Song, and Prabhava Upadrashta. 2020. *Private Equity, Consumers, and Competition: Evidence from the Nursing Home Industry.* SSRN Scholarly Paper ID 3626558. Rochester, NY: Social Science Research Network, June.

Gaugler, J. E. 2005. "Family Involvement in Residential Long-Term Care: A Synthesis and Critical Review." *Aging & Mental Health* 9, no. 2 (March): 105–118.

Gowrisankaran, Gautam, Ashley Langer, and Wendan Zhang. 2022. "Policy Uncertainty in the Market for Coal Electricity: The Case of Air Toxics Standards."

Grabowski, David C., Jonathan Gruber, and Joseph J. Angelelli. 2008. "Nursing Home Quality as a Common Good." *The Review of Economics and Statistics* 90, no. 4 (November): 754–764.

Greene, V. L., and D. J. Monahan. 1982. "The Impact of Visitation on Patient Well-Being in Nursing Homes." *The Gerontologist* 22, no. 4 (August): 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, February.

Hackmann, Martin B, R Vincent Pohl, and Nicolas R Ziebarth. 2021. "Patient Versus Provider Incentives in Long-Term Care," 87.

Hackmann, Martin B. 2019. "Incentivizing Better Quality of Care: The Role of Medicaid and Competition in the Nursing Home Industry." *American Economic Review* 109, no. 5 (May): 1684–1716.

Hansen, Lars Peter. 1982. "Large Sample Properties of Generalized Method of Moments Estimators." *Econometrica* 50 (4): 1029–1054.

Harrington, Charlene, Helen Carrillo, Rachel Garfield, Ellen Squires Published: Apr 03, and 2018. 2018. *Nursing Facilities, Staffing, Residents and Facility Deficiencies, 2009 Through 2016,* April.

Harrington, Charlene, Anne Montgomery, Terris King, David C Grabowski, and Michael Wasserman. 2021. *These Administrative Actions Would Improve Nursing Home Ownership And Financial Transparency In The Post COVID-19 Period.* http://www.healthaffairs.org/do/10.1377/forefront.2021

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 (April): 13–19.

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

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, nos. 3-4 (December): 273–299.

Huang, Sean Shenghsiu, and Richard A. Hirth. 2016. "Quality Rating and Private-Prices: Evidence from the Nursing Home Industry." *Journal of Health Economics* 50 (December): 59–70.

Ifrach, Bar, and Gabriel Y. Weintraub. 2017. "A Framework for Dynamic Oligopoly in Concentrated Industries." *The Review of Economic Studies* 84, no. 3 (July): 1106–1150.

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, no. 5 (May): 765–772.

Kwok, Jennifer H. 2019. "How Do Primary Care Physicians Influence Healthcare?," 96.

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, no. 5 (May): 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.

McFadden, Daniel. 1974. "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics.* New York: Academic Press.

———. 1981. "Econometric Models of Probabilistic Choice." *Structural Analysis of Discrete Data and Econometric Applications.*

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

Olenski, Andrew, and Szymon Sacher. 2022. *Estimating Nursing Home Quality with Selection.* SSRN Scholarly Paper, 4054786, Rochester, NY, March.

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

Pakes, Ariel, Michael Ostrovsky, and Steven Berry. 2007. "Simple Estimators for the Parameters of Discrete Dynamic Games (with Entry/Exit Examples)." *The RAND Journal of Economics* 38 (2): 373–399.

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, no. 5 (October): 589–596.

Rucinski, Tracy. 2018. "Illinois Nursing Homes Sue State over Low Medicaid Rates." *Reuters* (January).

Sabety, Adrienne. 2019. "The Value of Relationships in Healthcare," 78.

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

Schwab, Stephen D. 2021. "The Value of Specific Information: Evidence from Disruptions to the Patient- Physician Relationship," 40.

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* (March).

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* (March).

Syverson, Chad. 2011. "What Determines Productivity?" *Journal of Economic Literature* 49, no. 2 (June): 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, no. 5 (March): 933–940.

A Further Estimation Details

A.1 Profit Function Estimation

Estimation of the profit function $g(\theta)$ spans two datasets: (1) the national panel of accounting profits π_{jt}^{macro} and the observed state vector z_{jt} and (2) for the subset of facilities operating in Illinois 2012-2017, the model-implied profits $\hat{\pi}_{jt}^{micro}$ and states $\hat{z}_{jt}^{micro}$.

The moment conditions include:

$$\begin{aligned}
&\mathbb{E}\big[\pi_{jt}^{macro} - g(z_{jt};\theta)\big] = 0 \\
&\mathbb{E}\big[\pi_{jt}^{macro} - g(\hat{z}_{jt}^{micro};\theta)\big] = 0 \\
&\mathbb{E}\big[\hat{\pi}_{jt}^{micro} + \psi - g(z_{jt}^{micro};\theta)\big] = 0
\end{aligned}$$

With corresponding sample analogues:

$$\begin{aligned}
G_1^{macro} &= \frac{1}{N^{macro}} \sum_{j,t} \Big(\pi_{jt}^{macro} - g(z_{jt};\theta) \Big) \\
G_2^{macro} &= \frac{1}{N^{micro}} \sum_{j,t} \Big(\pi_{jt}^{macro} - g(\hat{z}_{jt}^{micro};\theta) \Big) \\
G_3^{micro} &= \frac{1}{N^{micro}} \sum_{j,t} \Big(\pi_{jt}^{micro} + \psi - g(\hat{z}_{jt}^{micro};\theta) \Big)
\end{aligned}$$

The non-linear profit function $g(z;\theta)$ includes one parameter for each point in the state space. I include an additional intercept ψ in the final set of micro moments to account for level differences in the reported profits and the model-implied profits. This yields $\dim(z) + 1 = 145$ parameters to estimate using $l = 3 \times \dim(z) = 432$ moments.

I stack G_1^{macro}, G_2^{macro}, and G_3^{micro}, and refer to the stacked l-dimensional row vector as:

$$G(\theta) = \Big[G_1^{macro}, G_2^{macro}, G_3^{micro} \Big]$$

The GMM estimator is then given by:

$$\hat{\theta}^{GMM} = \underset{\theta}{\operatorname{argmin}}\, G(\theta) W G(\theta)'$$

where W is an $l \times l$ weighting matrix. I follow the two-step feasible GMM approach, starting with the identity matrix to generate an initial estimate $\hat{\theta}_1$. Using these parameter estimates, I construct the variance-covariance matrices V_1, V_2, and V_3 for each of the three sets of moments, recalling that the sample sizes differ. I stack these diagonally and take the inverse to form the efficient weighting matrix $W = V^1(\hat{\theta}_1)$.

B Further Details on Counterfactuals

B.1 Simulation Details

Evaluating the impact of an increase in the Medicaid rate requires calculating new values of π_{jt}^{micro} with the scaled reimbursement rate. I adjust the national accounting profits using the product of the Medicaid share, the size of the rate increase, and the observed profits π_{jt}^{macro}. I then take the demand parameters as given, and estimate new θ parameters corresponding to the improved profitability. These parameters are used to compute new continuation values EV, plugging in the prior estimate of κ and the new θ estimates into equation (12). With the continuation values corresponding to higher Medicaid rates in hand, I then simulate the model. I iterate through the years, calculating the model-implied states in each year, and drawing new κ_{jt} values after each period. Facilities with draws of κ_{jt} above their discounted continuation value permanently exit the sample. Examining the effects of the targeted subsidy involves the same procedure as the first intervention, with the exception that I return to the initial θ parameters, and instead directly calculate a new continuation value for subsidized firms, noting that the continuation values are additive in the subsidy.

B.2 Computing Changes in Life Expectancy

In each of the counterfactual scenarios described in Section 7, the supply model generates a set of facilities predicted to exit, as well as their corresponding exit years. Using the MDS, I identify the long-stay residents in each facility in the year of predicted exit, following the approach described in Section 3 to identify the main analytic sample.

To compute the implied changes in life expectancy for these affected residents, for each resident-quarter I calculate fitted values of the mortality hazard given their demographic and health measures, denoted $\hat{h}_{it}^{\text{no exit}}$. These fitted values come from a Weibull survival model, which I train using the control group cohort described in Section 3, as this cohort is not contaminated by any effects of realized nursing home closures.

I also construct a counterfactual hazard rate, relying on the effects estimated from equation (1): $\hat{h}_{it}^{\text{exit}} = \hat{h}_{it}^{\text{no exit}} + \hat{\beta}^t$. With these hazards in hand, I calculate the expected change in life expectancy as:

$$\mathbb{E}[\Delta LE_i] = \mathbb{E}[LE_i^{\text{exit}}] - \mathbb{E}[LE_i^{\text{no exit}}]$$

where

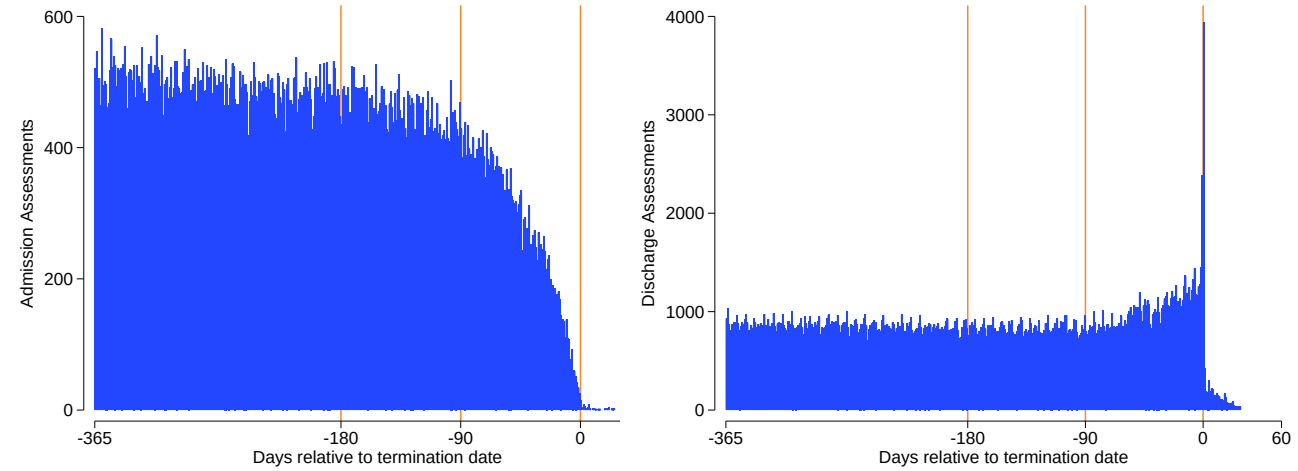
$$LE_i^{\text{exit}} = \sum_{t}^{T-1} \left[\prod_{\tau=1}^{t} (1 - d_{i\tau}^{\text{exit}}) \right] + \mathbb{E}[S_{iT}^{\text{exit}}] \prod_{\tau=1}^{T} (1 - d_{i\tau}^{\text{exit}})$$

$$LE_i^{\text{no exit}} = \sum_{t}^{T-1} \left[\prod_{\tau=1}^{t} (1 - d_{i\tau}^{\text{no exit}}) \right] + \mathbb{E}[S_{iT}^{\text{no exit}}] \prod_{\tau=1}^{T} (1 - d_{i\tau}^{\text{no exit}})$$

$$\mathbb{E}[S_{iT}] = \frac{\Gamma(1 + \frac{1}{\alpha})}{\left(\frac{h_{iT}}{\alpha} T^{1-\alpha}\right)^{\frac{1}{\alpha}}}$$

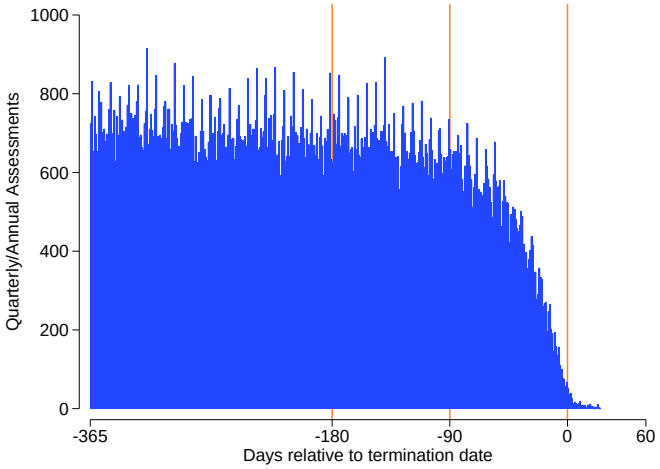
where $d_{i\tau}$ indicates death in period τ, and $\mathbb{E}[d_{i\tau}] = h_{i\tau}$, T indicates the last period, and Γ denotes the gamma function.

C Additional Tables and Figures



(a) Admissison Assessments

(b) Discharge Assessments



(c) Quarterly/Annual Assessments

Figure C.1: 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.

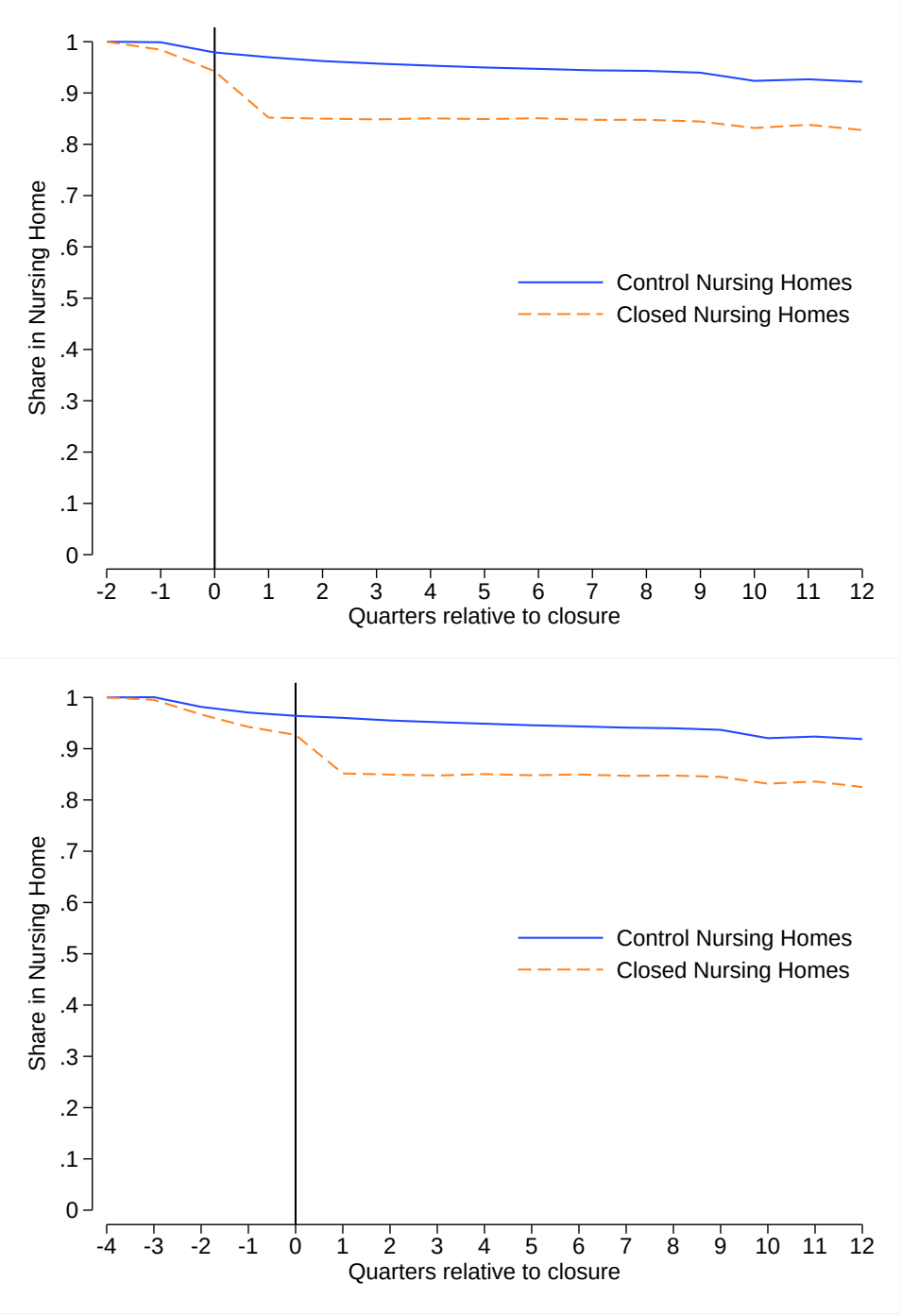


Figure C.2: Share of surviving cohort still present in a nursing home

Notes: Figures present the empirical share of residents who are still in a nursing home. Top panel includes residents in the baseline cohort; bottom panel includes residents who were in the facility four quarters prior to closure.

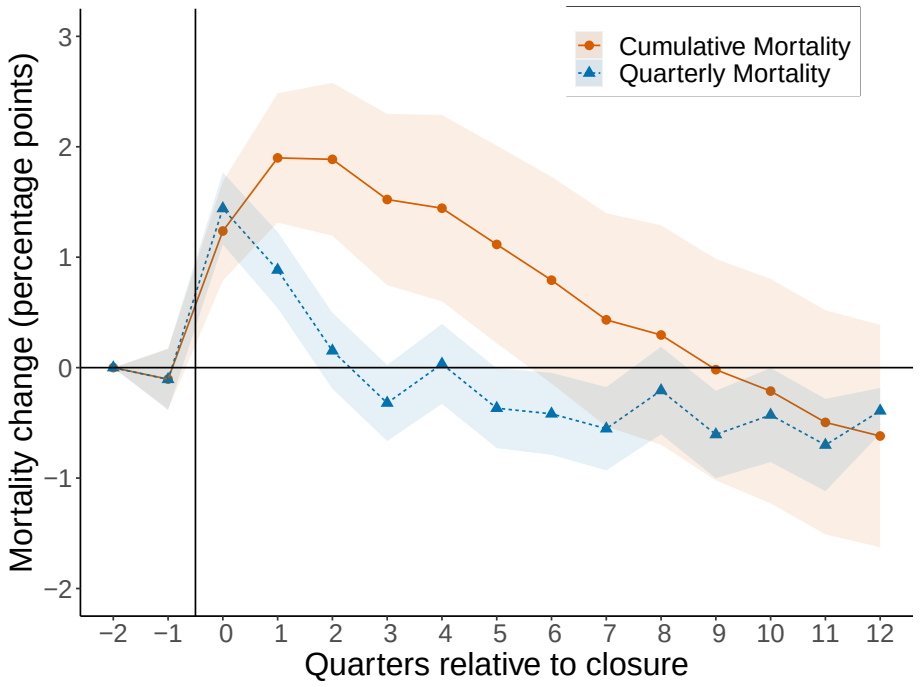
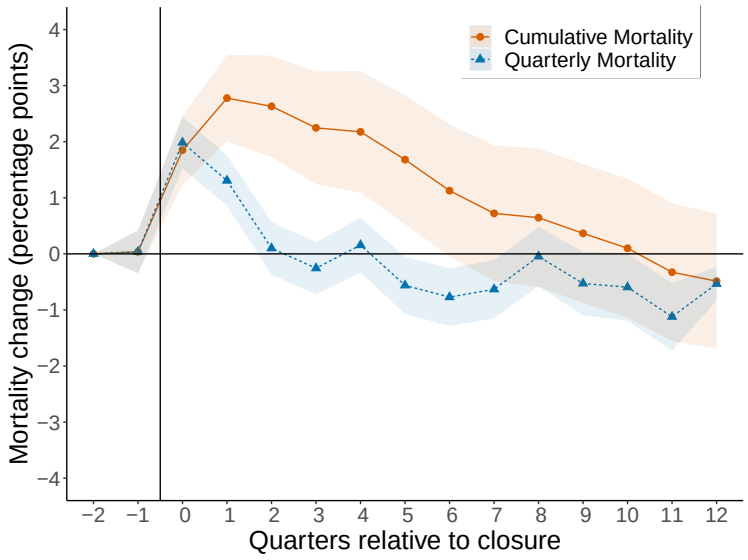
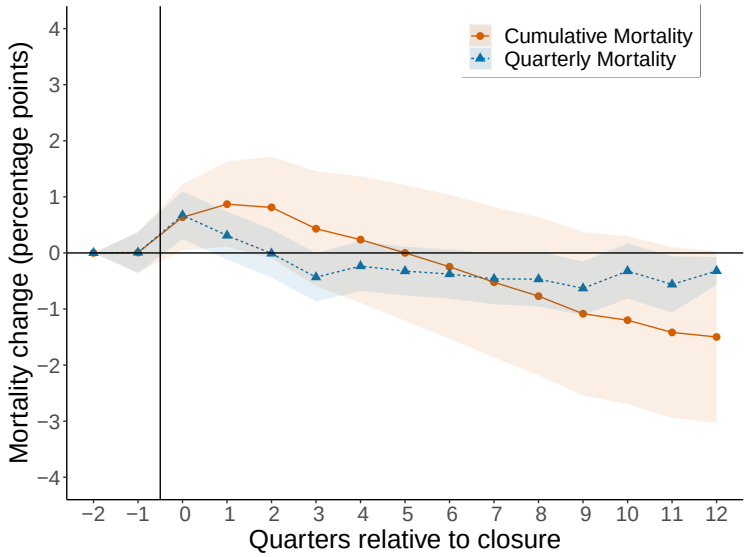


Figure C.3: Mortality rate relative to closure

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.



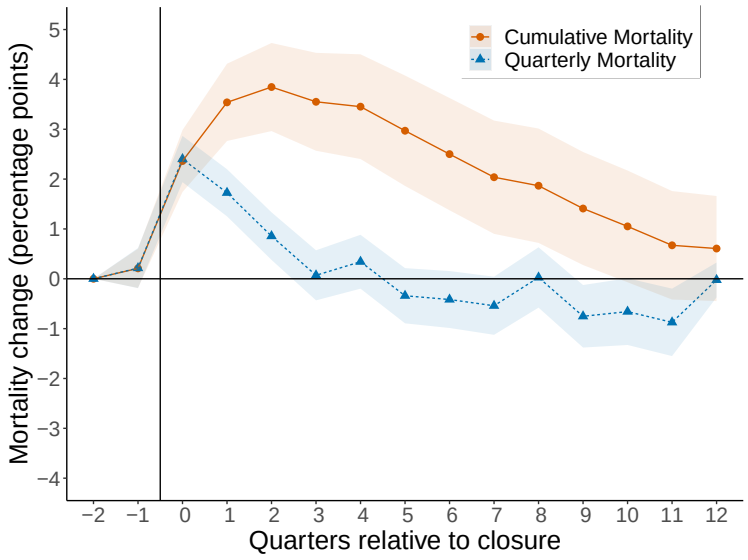
(a) Alzheimer's/Dementia



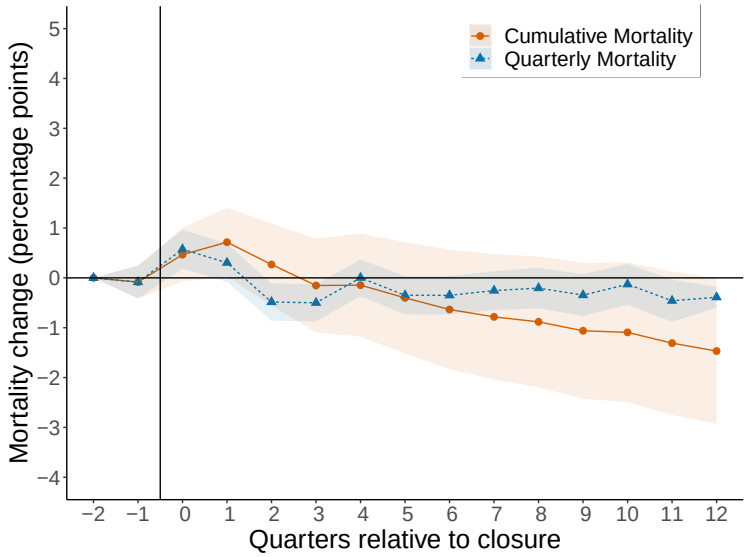
(b) No Alzheimer's/Dementia

Figure C.4: Mortality change by dementia diagnosis

Notes: Figures present estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort by the presence of a diagnosis for Alzheimer's or other dementia at the time of closure.



(a) Age $\geq$ 80 Years Old



(b) Age $<$ 80 Years Old

Figure C.5: Mortality change by initial age

Notes: Figures present estimates from equation (1) along with the cumulative mortality estimates (ΔM_t) for the baseline resident cohort by the age of the resident at the time of closure. Top panel includes residents who are 80 years old or older at the time of closure. Bottom panel includes residents who are younger than 80 years old at the time of closure.

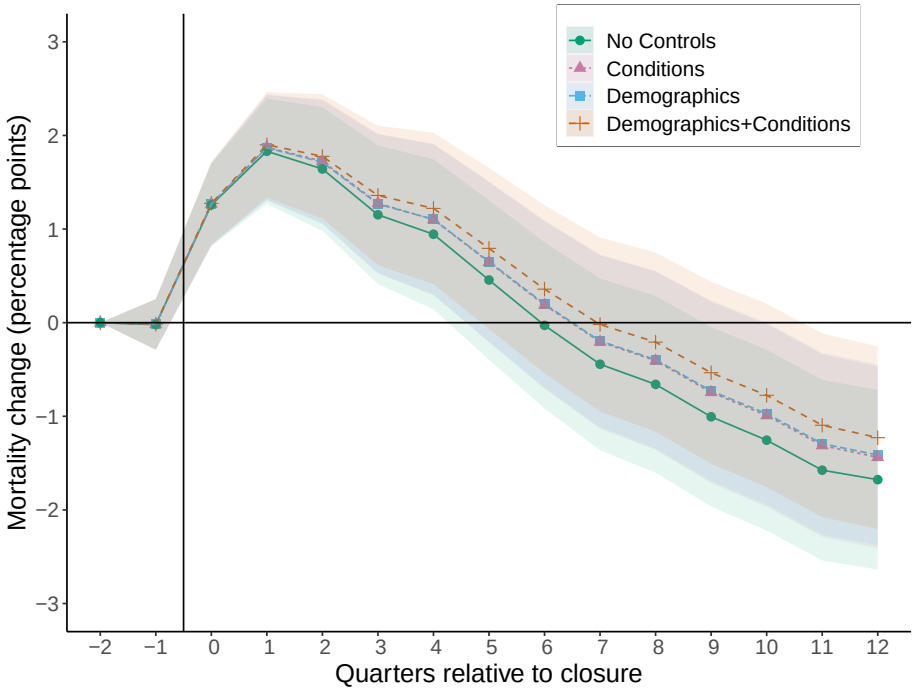


Figure C.6: Test of Coefficient Stability

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.

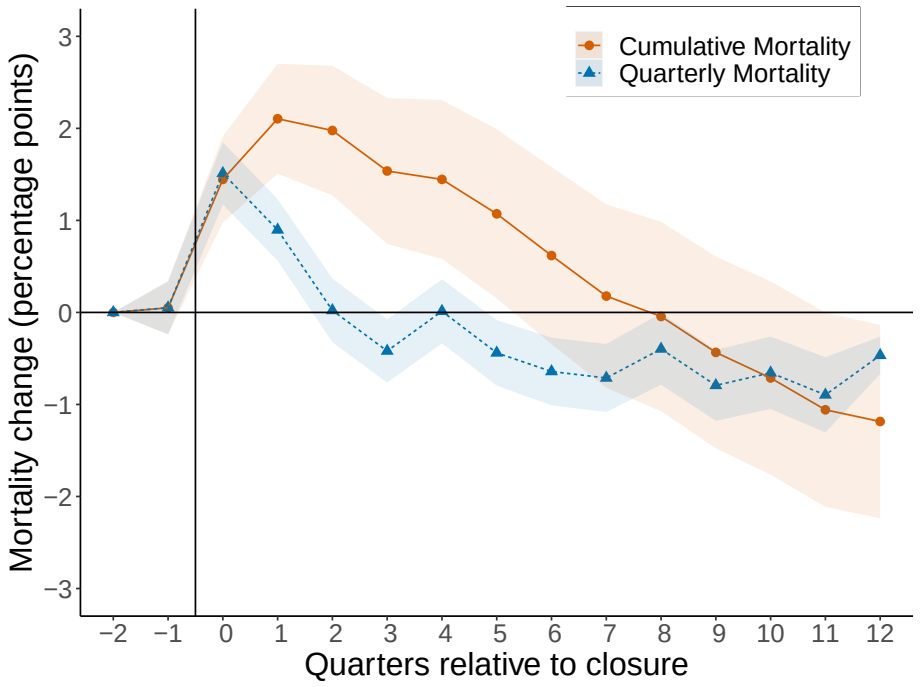


Figure C.7: Mortality effect with claims-derived controls

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.

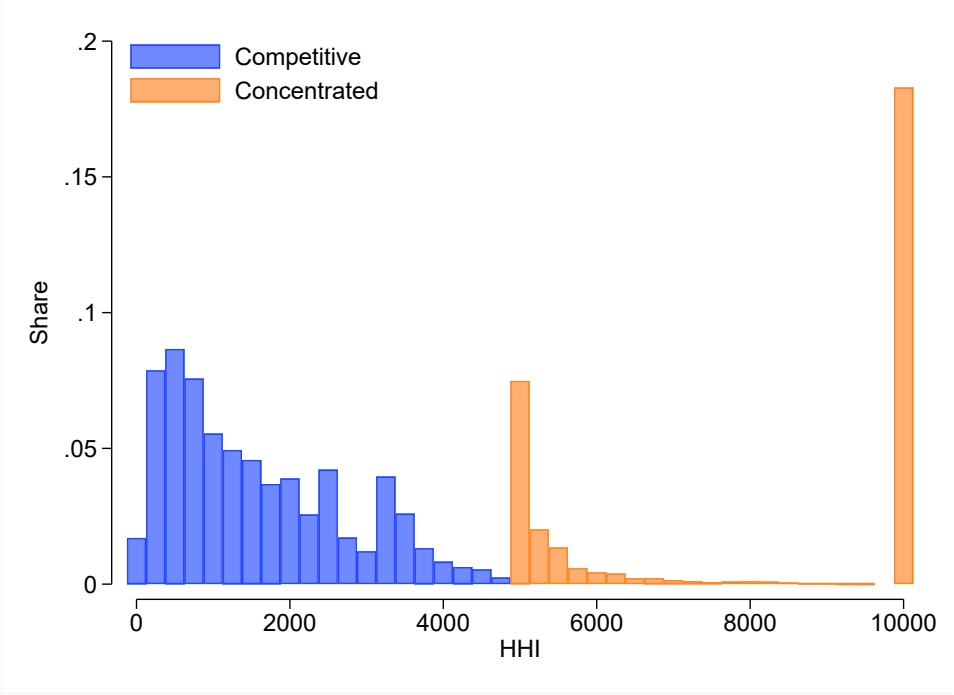


Figure C.8: Distribution of HHI in year prior to exit among analysis sample

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.

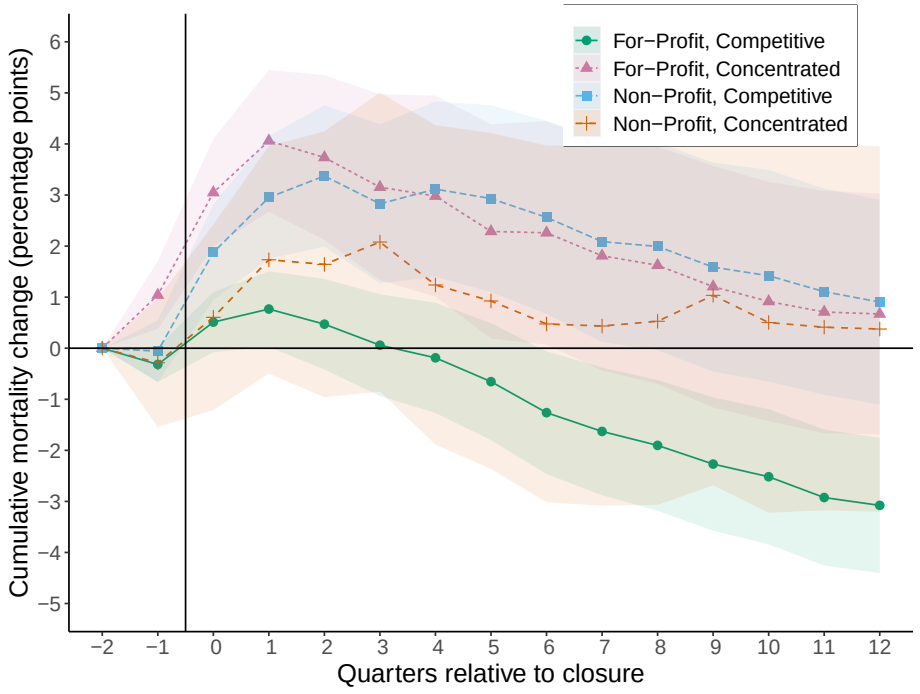
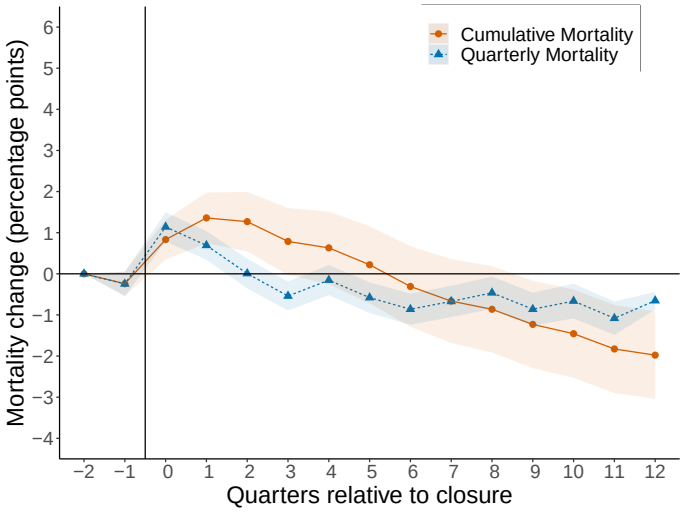
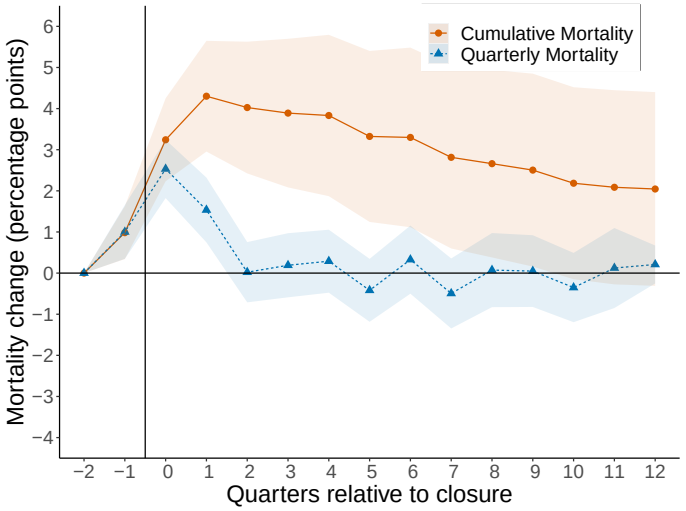


Figure C.9: Cumulative mortality by concentration and ownership status

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) Competitive Markets



(b) Concentrated Markets

Figure C.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.

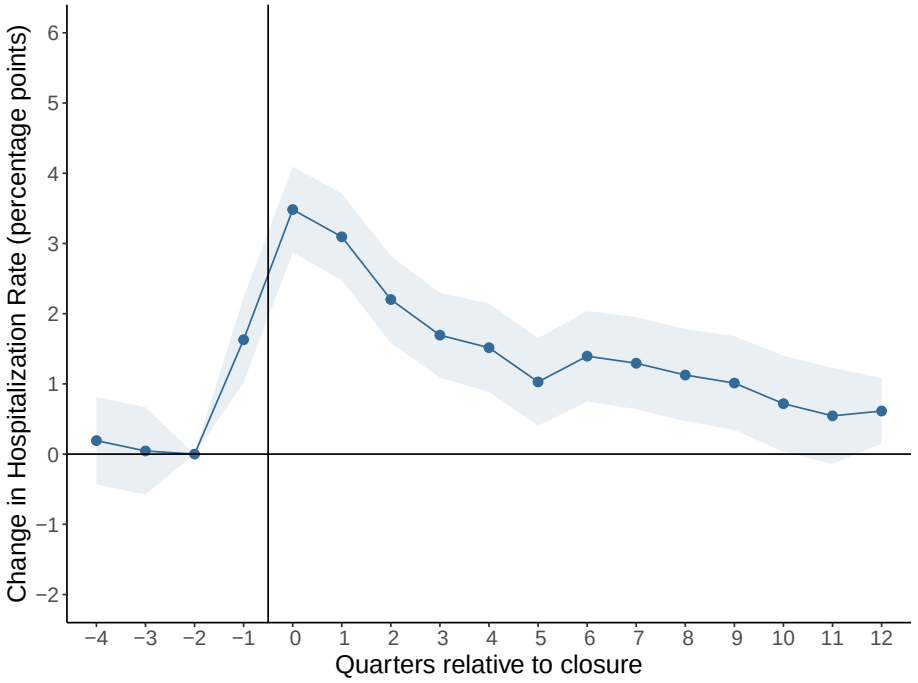


Figure C.11: Hospitalization rate

Notes: Figure presents the results from estimating equation (1) using the baseline resident cohort. The dependent variable is an indicator for any acute care short-stay hospitalization in the quarter.

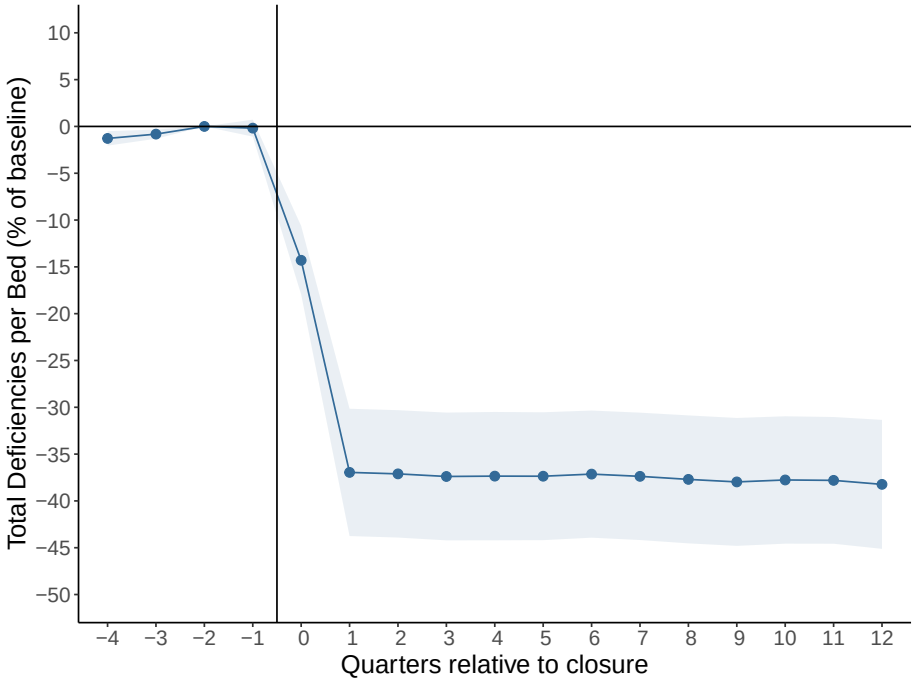


Figure C.12: Total Deficiency Citations

Notes: Figures present how patients reallocate following their displacement from a closing nursing home. This figure is the total deficiencies analogue to panel (a) of Figure 6 in the main text, which is restricted to only quality of care violations. Patients who do not transfer to a new nursing home are excluded.

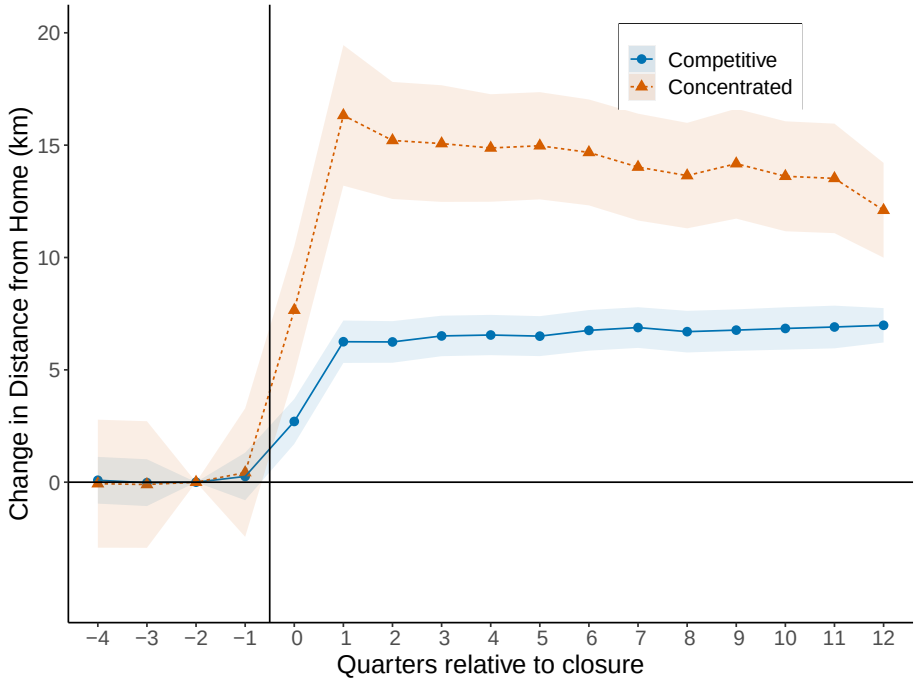


Figure C.13: Distance from home zip code

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.

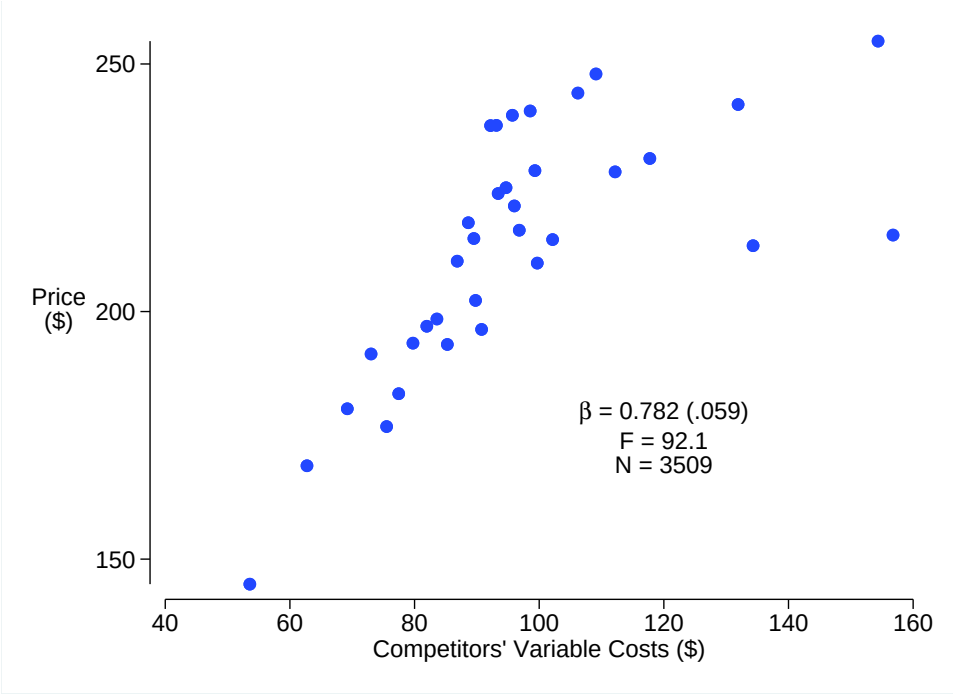


Figure C.14: Price Sensitivity First Stage

Notes: Figure presents the first stage results from estimating the price sensitivity parameter α^p described in Section 6.2. The observations correspond to facility-years, the dependent variable is facility j's private price, and the instruments are the average variable costs of other firms in the county.

Data Source	Years	Relevant Data	Application
MDS	2000-2017	Demographics, health measures, nursing home stays	Mortality effects, demand estimation
BSF	2000-2017	Mortality dates, home zip codes, health measures, Medicaid eligibility	Mortality effects, demand estimation
MedPAR	2000-2017	Hospital admission, Medicare coverage	Hospitalization effects, identifying payer type
LTCFocus	2000-2019	Nursing home characteristics	Mortality effects, supply estimation
Deficiency Surveys	2006-2017	Deficiency citations	Mortality effects
Medicare Cost Reports	2011-2019	Nursing home financials	Supply estimation
Illinois Medicaid Cost Reports	2012-2017	Private prices and Medicaid rates	Demand estimation

Table C.1: Data Sources

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

	Closed Firms (1)	Matched Firms (2)	All Non-Closed Firms (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 C.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.

Occupancy (%)	Medicaid (%)	Quartile 1	Quartile 2	Quartile 3	Quartile 4
		(1)	(2)	(3)	(4)
		Including Micro-Moments			
Low	Low	27.96	28.11	30.76	31.85
Low	High	28.25	16.97	24.82	28.98
High	Low	36.43	50.69	44.05	62.35
High	High	29.84	28.92	33.33	34.15
		Excluding Micro-Moments			
Low	Low	17.92	25.92	36.39	46.00
Low	High	13.04	15.31	19.00	25.65
High	Low	32.25	45.03	52.42	71.57
High	High	25.40	28.78	36.54	46.56

Table C.3: Profit function θ estimates

Notes: Table reports a subset of the profit function estimates θ at select points in the state space. Quartiles refer to the quartile of the county fixed effect. "Low" and "high" occupancy rates and Medicaid shares correspond to the bottom and top quantiles in the state space. The top panel reports the value of θ computed using all the moments described in Appendix Section A.1. The bottom panel presents results excluding the micro-moments exclusive to the Illinois facilities.

Occupancy (%)	Medicaid (%)	Quartile 1	Quartile 2	Quartile 3	Quartile 4
		(1)	(2)	(3)	(4)
		Including Micro-Moments			
Low	Low	307.85	286.25	313.65	335.41
Low	High	306.59	256.81	293.37	323.12
High	Low	339.15	357.60	368.07	424.32
High	High	333.86	312.39	340.34	369.63
		Excluding Micro-Moments			
Low	Low	201.91	261.11	321.09	412.58
Low	High	187.15	231.89	278.20	357.01
High	Low	261.14	337.60	398.16	512.54
High	High	242.60	295.90	352.96	446.53

Table C.4: Continuation value EV estimates

Notes: Table reports a subset of the continuation values EV at select points in the state space. Quartiles refer to the quartile of the county fixed effect. "Low" and "high" occupancy rates and Medicaid shares correspond to the bottom and top quantiles in the state space. The top panel reports the value of EV computed using all the moments described in Appendix Section A.1. The bottom panel presents results excluding the micro-moments exclusive to the Illinois facilities.