Owner Incentives and Performance in Healthcare: Private Equity Investment in Nursing Homes

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Abstract

Amid an aging population and a growing role for private equity (PE) in elder care, this paper studies how PE ownership affects U.S. nursing homes using patient-level Medicare data. We show that PE ownership leads to lower-risk patients and increases mortality. After instrumenting for the patient-nursing home match and conducting a marginal treatment effects analysis, we recover an average treatment effect on mortality of 5%. Declines in measures of patient well-being, nurse staffing, and compliance with care standards help to explain the mortality effect. Overall, we conclude that PE has nuanced effects, with adverse outcomes for a subset of patients.

1 Introduction

The U.S. population, like that of many advanced economies, is aging rapidly. This has created increasing demand for elderly care. Private equity (PE)-owned firms are playing a growing role in meeting this need. In this paper, we examine how PE ownership of nursing homes affects Medicare patients and taxpayers. Relative to independent private firms, PE ownership brings short-term, high-powered incentives to maximize profits. Existing literature and the policy debate provide opposing predictions.

On the one hand, there is evidence that for-profit healthcare firms can maintain long-term implicit contracts with stakeholders (Duggan, 2000; Adelino et al., 2015). Voices from the private sector suggest this may apply to PE; for example, a 2019 report from consulting firm EY concluded that "Not only is PE perceived to have a beneficial overall impact on health care businesses, it is also considered to positively influence the focus on quality and clinical services." Finally, PE has been found to have positive effects in other industries (Kaplan, 1989; Kaplan and Weisbach, 1992; Davis et al., 2014; Bloom et al., 2015; Bernstein and Sheen, 2016; Hochberg and Rauh, 2013).

On the other hand, nursing home customers are particularly vulnerable and face severe information frictions (Carlin et al., 2020). In contexts where financial literacy is lacking or decision-making is impaired by cognitive decline, consumers may make choices that are not in their interest (Carlin and Robinson, 2012). This could lead to different outcomes than in other parts of healthcare and the economy more broadly. Theories of firm behavior suggest that information frictions and non-contractible quality can weaken the natural ability of a market to align firm incentives with consumer welfare (Arrow, 1963; Hansmann, 1980; Hart et al., 1997). In 2019, U.S. Senators asked about "the role of PE firms in the nursing home care industry, and the extent to which these firms' emphasis on profits and short-term return is responsible for declines in quality of care."

In this paper, we assess the effects of PE ownership on U.S. nursing homes. Within healthcare, nursing homes represent an extreme example of reliance on subsidy and market frictions. First, the average nursing home receives 75% of its revenue from the government. Second, patients are especially vulnerable and exhibit a strong tendency to go to the closest facility (Grabowski et al., 2013). The sector is also independently important, with spending at $166 billion in 2017 and projected to grow to $240 billion by 2025 (Martin et al., 2018). PE firms have acquired both large chains and independent facilities, enabling us to make progress on isolating the effects of PE ownership from corporatization (Eliason et al., 2020).

We use patient- and facility-level administrative data from the Centers for Medicare & Medicaid Services (CMS), which we match to PE deal data. The data include about 18,300 unique nursing homes between 2000 and 2017. Of these, 1,674 were acquired by PE firms in 128 unique deals. Our analysis sample contains 5.3 million unique short-stay patients. We focus on Medicare, which accounts for about 60% of the unique patients that enter a nursing home during our sample period.

There are two empirical challenges to estimating the causal effects of PE ownership. The first is non-random selection of acquisition targets. We partially address this by including facility fixed effects in estimation, which eliminates time invariant differences across facilities and their local markets. We also include patient market-by-year fixed effects to mitigate concerns about unobserved differential trends in market structure across locations. Finally, we present event studies and assess pre-trends for all outcomes. The results point to causal effects on treated firms, though these are not necessarily externally valid to a random firm in the economy.[1] This interpretation is nonetheless important for social welfare as private equity expands its footprint; even if target firms "need" a buyout because they are unobservably underperforming, our results raise questions for a social planner trading off patient well-being against firm value.

The second challenge is that the patient composition changes after PE buyouts. We find that patient risk declines, which could reflect an effort to pursue more financially attractive patients. While Medicare compensates nursing homes for the higher costs of serving more complex patients by adjusting payments, these adjustments account for only a fraction of the variance

[1] As we show below, PE target facilities were larger, located in urban markets, served more patients per bed and had a more lucrative payer mix – all prior to the buyout.

in costs (White et al., 2002). Medicare also rewards physical therapy, which favors healthier patients (Carter et al., 2012). Following PE buyouts, we find declines in measures associated with costly care such as cognitive impairments and inability to perform daily living activities (Hackmann et al., 2018). To address potential unobserved selection, we control for the patient-facility match with a differential distance instrumental variables (IV) strategy (McClellan et al., 1994; Grabowski et al., 2013; Card et al., 2019), exploiting patient preference for a nursing facility close to their home (the median distance is 4.6 miles). The distance-based instrument strongly predicts facility choice and is uncorrelated with observed patient risk. It identifies a causal effect within the population of patients who go to a nursing home because it is the closest one to their home.

We use both OLS and IV differences-in-differences models to examine the effects of PE buyouts on patient welfare. The most important and objective measure in our context is short-term survival, which we define as the probability of death during the stay and the following 90 days (McClellan and Staiger, 1999; Hull, 2018). In OLS models, we show that PE ownership leads to a 0.3 pp increase in mortality, which is about 2% of the mean. The IV approach finds that going to a PE-owned nursing home has a much larger effect on mortality of 13% of the mean. This effect is detectable as early as 15 days following discharge and is stable out to 365 days.

We take a step toward reconciling the smaller OLS and larger IV results using a marginal treatment effects (MTE) analysis. Unlike the IV LATE, the MTE analysis estimates parameters that are not specific to the complier group and allows us to make more general statements regarding the causal effects of PE ownership within the treated sample of facilities. The MTE analysis recovers an average treatment effect of 0.9 pp. This implies that a randomly chosen Medicare patient from our sample would experience a 5% increase in the chance of short-term mortality if she goes to a PE-owned nursing home, which is just over twice the OLS effect, but less than half the IV effect. The MTE also reveals substantial heterogeneity in treatment effects, including beneficial effects for some types of patients.

We assess whether the results are driven by the related but distinct phenomenon of corporatization. The coefficients remain intact when we restrict our attention to PE acquisitions of the largest chains, in which chain size remained constant over the sample period, implying that the effect captures the nature of ownership rather than consolidation or corporatization. We also conduct standard robustness tests, including a placebo analysis, where we show there are no pre-buyout effects. Together with the absence of pre-trends in event studies, this suggests that the results do not reflect the targeted facilities being on track to experience these effects regardless of the buyout.

We examine three channels to explain and corroborate the effects on mortality. The first is nurse availability, which is the most important determinant of quality of care (Zhang and Grabowski, 2004; Lin, 2014). PE ownership leads to a 3% decline in hours per patient-day supplied by the frontline nursing assistants who provide the vast majority of caregiving hours and perform crucial well-being services such as mobility assistance, personal interaction, and cleaning to minimize infection risk. We also find that relatively lower risk patients drive the negative average effects on mortality, which may reflect lower frontline nurse availability. PE-owned nursing homes also keep low-risk patients longer, which would maximize Medicare revenue but may be worse for the patient. Among high-risk cohorts, PE-owned nursing homes appear to maintain quality, as they increase the number of RNs, who are responsible for the most medicalized aspects of treatment.

The second channel is facility Five Star ratings, which are constructed by CMS to provide summary information on quality of care. We find negative effects on these ratings. A disconnect between demand and quality of care may reflect information frictions in nursing home quality transparency. Existing work finds weak or no demand response to information about nursing home care quality, including Five Star Ratings (Grabowski and Town, 2011; Werner et al., 2012). Consistent with an important role for subsidies—which separate revenue from the consumer—as a mechanism for the negative effects, we find that quality declines are driven by nursing homes with above-median Medicare funding as a share of total revenue.

If PE ownership affects mortality by leading to a lower quality of care, we expect negative effects on measures of patient well-being. To investigate this third channel, we consider three measures of patient well-being that are key standards for CMS. In OLS (IV) models, we find a decrease in mobility of 6.2% (4%), increase in ulcer development of 10% (0%), and increase in pain intensity of 9% (12%). Event studies indicate no pre-trends and show discontinuous changes after the buyouts. This third channel corroborates the effect on mortality, even though there are differences between the OLS and IV models.

Taken together, our results indicate nuanced effects of PE ownership. Patients become less risky after PE buyouts and thus it is unsurprising to see a smaller effect on mortality in OLS relative to IV analysis. The baseline OLS results and MTE analysis show that for many patients, there is no appreciable effect on mortality. However, we do find a large increase in mortality for compliers with the instrument, who may be more vulnerable given that they go to the closest nursing home rather than demonstrate the resources or capacity to choose one farther away. Overall, it seems likely that PE ownership either does not affect or benefits more sophisticated patients, but adversely affects those who face more information frictions.

To understand implications for the taxpayer and to shed light on how PE firms create value, we assess the financial strategies of PE-owned nursing homes. Consistent with patients being on average lower risk, OLS models find small declines in the amount billed to Medicare per stay (note profits may increase if caring for these patients is less costly). In contrast, the IV estimate is in the opposite direction, indicating a 10% increase in the amount billed. We also use facility finances to explore why nursing homes are attractive targets for PE buyouts given their low and regulated profit margins, often cited at just 1-2%. Using CMS cost reports, we find that there is no effect of buyouts on net income, which is puzzling. There are three types of expenditures that are particularly associated with PE profits and tax strategies: “monitoring fees" charged to portfolio companies, lease payments after real estate is sold to generate cash flows, and interest payments reflecting the importance of leverage in the PE business model (Metrick and Yasuda, 2010; Phalippou et al., 2018). We find that all three types of expenditures increase after buyouts, with interest payments rising by over 200%. While many aspects of facility finances, including labor costs and overall revenue, are either sparsely populated or ambiguously documented in the cost reports, the elements that we can analyze point to changing financial strategies that could enable attractive returns for the PE fund without increasing reported net income of the facility.

This paper contributes to multiple literatures. Most broadly, our results imply that high-powered incentives to maximize profits are not unambiguously beneficial in contexts with market frictions and government subsidy, which may be helpful for policymakers considering actions to improve transparency and accountability (Rose-Ackerman, 1996; Picone et al., 2002; Bénabou and Tirole, 2006; Curto et al., 2019). We contribute to work on how firm ownership interacts with price incentives and regulation in healthcare (Dafny et al., 2012; Ho and Pakes, 2014; Eliason et al., 2018; Ho and Lee, 2019; Curto et al., 2021). Although economic theory predicts that for-profit and thus PE-owned firms may be more likely to compromise on the quality of care, the empirical evidence has been mixed.[2] Within healthcare, our paper joins work on nursing homes, which grow more economically important as the population ages (Grabowski et al., 2008, 2013; Lin, 2015; Hackmann et al., 2018; Hackmann, 2019). Our results imply that owner incentives are of first-order importance, pointing to possible benefits from government reimbursements that target patient outcomes. These issues have become more urgent as the COVID-19 pandemic has exposed systemic flaws at long-term care facilities, which account for nearly 40% of U.S. deaths from the virus.[3]

Finally, we add to work on how PE ownership affects target firm operations (Boucly et al., 2011), product quality (Lerner et al., 2011; Eaton et al., 2020; Fracassi et al., 2020), and value (Gupta and Van Nieuwerburgh, 2019; Bernstein et al., 2019; Biesinger et al., 2020). There is existing work on the role of PE in healthcare that has reached mixed conclusions, and broadly finds no differential effects. However, these studies have faced challenges of limited geographies, a short sample period, a lack of patient-level data, or a small number of deals (Stevenson and Grabowski, 2008).[4] To our knowledge, no national study on PE or on ownership in healthcare has simultaneously addressed both facility-level and patient-level selection.

[2] In addition to work mentioned above, see Grabowski and Hirth (2003), Jones et al. (2017), Hill et al. (2019), Kunz et al. (2020), and Capps et al. (2020).

[3] Source: The New York Times Coronavirus Tracker, as of October 2020.

[4] Also see Harrington et al. (2012); Pradhan et al. (2013, 2014); Cadigan et al. (2015); Huang and Bowblis (2019); Gondi and Song (2019); Casalino (2020); Gandhi et al. (2020)

The paper proceeds as follows. Section 2 provides institutional background. Section 3 describes the data. The strategy for patient-level analysis is explained in Section 4, and the results are in Section 5. The facility-level estimation is in Section 6. Section 7 concludes.

2 Institutional Background

2.1 The Economics of Nursing Homes

Nursing homes provide both short-term rehabilitative stays – usually following a hospital procedure – as well as long-term custodial stays for patients unable to live independently. There are two unique features of the long-term care market in the U.S. relative to other healthcare subsectors. First, government payers (Medicaid and Medicare) account for 75% of revenue, while private insurance plays a much larger role in other subsectors (Johnson, 2016).[5] Second, about 70% of nursing homes are for-profit, which is a much larger share than other subsectors. For example, fewer than one-third of hospitals are for-profit. Policymakers have long been concerned about low-quality care at nursing homes in the U.S. and for-profit ownership has often been proposed as a causal factor (Institute of Medicine, 1986; Grabowski et al., 2013).[6]

As with any business, the economics of nursing homes are shaped by the nature of demand, the cost structure, and the regulatory environment. On the demand side, nursing homes serve elderly patients but are paid by third-party, largely government payers. Over 95% of facilities treat both Medicare and Medicaid patients (Harrington et al., 2018). Both programs pay a prospectively set amount per day of care for each covered patient ('per diem'), which does not incorporate quality of care, reputation, or other determinants that would be considered by a

[5]Medicare is an entitlement health insurance program for Americans above age 65. It covers short-term rehab care following hospital inpatient care, and accounts for about 60% of the unique patients that enter a nursing home, and 15% of overall patient-days in our data. Medicaid is a means-tested insurance program targeted at low income and disabled non-elderly individuals, accounting for about 60% of nursing home patient-days.

[6]This concern is frequently reflected in the popular media, including as a reason for high death rates from Covid-19 in nursing homes. For example, a *New York Times* article in December, 2020 asserted that: *"Long-term care continues to be understaffed, poorly regulated and vulnerable to predation by for-profit conglomerates and private-equity firms. The nursing aides who provide the bulk of bedside assistance still earn poverty wages, and lockdown policies have forced patients into dangerous solitude"* (Kim, 2020).

well-functioning market. These rates are non-negotiable, and facilities simply choose whether they will accept the beneficiaries of these programs. Medicare fee-for-service pays much more, at roughly $515 per patient day relative to $209 per patient day from Medicaid.[7] Overall profit margins are in the low single digits (MedPAC, 2017), a topic we return to at the end of the paper.

Nursing homes provide institutional care and so have high fixed costs, making the occupancy rate an important driver of profitability. Nursing staff represent the largest component of operating cost, at about 50% (Dummit, 2002). Broadly speaking, there are three types of nurses. Low-skill Certified Nurse Assistants (CNAs) account for about 60% of total staff hours and provide most of the direct patient care. Licensed Practical Nurses (LPNs) have more training and experience than CNAs but cannot manage patients independently. Registered Nurses (RNs) have the highest skill and experience levels, and can independently determine care plans for patients. LPNs and RNs each account for about 20% of nurse hours. Nurse availability is crucial to the quality of care and there is a consensus that low ratios of nursing staff to residents are associated with higher patient mortality and other adverse clinical outcomes (Tong, 2011; Lin, 2014; Friedrich and Hackmann, 2017). Staffing ratios are therefore standard metrics to examine nursing home quality.

There is information asymmetry between patients and healthcare providers (McGuire, 2000). As comparing nursing homes on quality is difficult and price is not a helpful signal, reputation may play a large role in nursing home demand (Arrow, 1963). Profit maximizing facilities might invest in high-quality care to build and sustain their reputation, yet face a dynamic incentive problem because they can generate higher profits in the short-term by cutting patient care costs. It is unclear which inputs affect nursing home reputation, but prior studies suggest that patient demand does not respond to poor quality scores on government mandated report cards, potentially leaving short-term incentives to prevail (Grabowski and Town, 2011; Werner et al., 2012).

[7] https://skillednursingnews.com/2019/03/medicare-advantage-eats-into-margin-gains-for-skilled-nursing-facilities/. Medicaid still pays more than the marginal cost of treatment per day. Hackmann (2019) calculates that the marginal cost of treatment per-day is about $160 on average.

2.2 The Economics of Private Equity Control

PE firms conduct leveraged buyouts (LBOs), in which a target firm is acquired primarily with debt financing – which is placed on the target firm's balance sheet – and a small portion of equity.[8] PE is associated with particularly high-powered incentives to maximize profits in part because the General Partners (GPs) who manage PE funds are compensated through a call option-like share of the profits (Kaplan and Stromberg, 2009). Specifically, their compensation stems primarily from the right to 20% of profits from increasing portfolio company value between the time of the buyout and an exit, when the company is sold to another firm or taken public. GPs also receive transaction and monitoring fees, which are not tied to performance. However, deals are typically not successful if the business continues as-is, motivating aggressive and short-term value-creation strategies. In contrast, a traditional business owner running the firm as a long-term going concern with less leverage may prefer lower but more stable profits.

A large literature in finance has shown that PE buyouts increase productivity, operational efficiency, and generate high returns.[9] Kaplan and Stromberg (2009) argue that PE owners increase firm value through three channels, which they call financial, governance, and operations engineering. The first channel includes alleviating credit constraints, which may enable more investment (Boucly et al., 2011), and exploiting the favorable tax treatment of debt (Spaenjers and Steiner, 2020). Governance engineering includes changes to the compensation, benefits, and composition of the management team at the target firm to align their incentives with those of the PE owners, for example instituting equity-based compensation (Gompers et al., 2016). Bloom et al. (2015) show that PE-owned firms are better managed than similar firms that are not PE-owned. In operations engineering, GPs apply their business expertise to add value to their investments. For example, they might invest in new technology, expand to new markets, and cut costs (Gadiesh and MacArthur,

[8] Kaplan and Stromberg (2009) provide a detailed discussion of the PE business model and review the academic evidence on their effects. In the interest of brevity, we limit our discussion.

[9] See Kaplan (1989); Kaplan and Schoar (2005); Guo et al. (2011); Acharya et al. (2013); Harris et al. (2014); Bernstein and Sheen (2016); Robinson and Sensoy (2016); Korteweg and Sorensen (2017); Eaton et al. (2020).

2008; Acharya et al., 2013; Bernstein and Sheen, 2016). Davis et al. (2014) show that after PE buyouts, firms expand efficient operations while closing inefficient ones.

Considering these changes in the context of nursing homes, the effects of PE ownership on patients are theoretically ambiguous. On the one hand, better management, stronger incentives, and access to credit may lead to improvements in care quality. On the other hand, three forces could adversely affect quality. First, cost cutting measures and a focus on capturing subsidies could come at the expense of quality improvement. Second, large interest payments stemming from the new debt obligations may reduce cash available for care. Relatedly, since PE owners often sell real estate assets shortly after the buyout to generate cash that can be returned to investors, the nursing home may also take on the additional cost of rent. Such cash flows early in the deal's lifecycle boost ultimate discounted returns. For example, in one of the largest PE deals in our sample, the Carlyle Group bought HCR Manorcare for about $6.3 billion in 2007, of which roughly one quarter was equity and three-quarters were debt. Four years later, Carlyle sold the real estate assets for $6.1 billion, offering investors a substantial return on equity (Keating and Whoriskey, 2018). Afterward, HCR Manorcare rented its facilities; the monthly lease payments are essentially another debt obligation, and a Washington Post investigation found that quality of care deteriorated following the real estate sale (Keating and Whoriskey, 2018). The third force is the relatively short-term time horizon, which could push managers to maximize short-term profits at the expense of long term performance. In the case of HCR Manorcare, the nursing home chain was ultimately unable to make its interest and lease payments and entered bankruptcy proceedings in the spring of 2018. Carlyle sold its stake to the landlord.

3 Data and Descriptive Statistics

In this section we briefly summarize our data sources and provide descriptives about the sample, including an analysis of PE targeting. In Appendix A, we describe these elements in comprehensive detail.

3.1 Data

We obtain facility-level annual data between 2000 and 2017 from publicly-available CMS sources. In each year we observe about 15,000 unique skilled nursing facilities (we use the term “nursing home" interchangeably), for a total of approximately 280,000 observations. These data include variables such as patient volume, nurse availability, and various components of the Five Star ratings, which first appear in 2009. Approximately half of the PE deals in our sample occurred after 2009.

Our second data source consists of patient-level data for Medicare beneficiaries from 2004 to 2016. We use the Medicare enrollment and claims files (hospital inpatient, outpatient, and nursing homes) for the universe of fee-for-service Medicare beneficiaries. We merge these files with detailed patient assessments recorded in the Minimum Data Set (MDS). These data are confidential and were accessed under a data use agreement with CMS. They include patient enrollment details, demographics, mortality, and information about nursing home and hospital care during this period.

In patient-level analysis, the unit of observation is a nursing home stay that begins during our sample period, which starts in 2005 in order to have at least one look-back year. We consider only the patient’s first nursing home stay in our entire sample period so that we can unambiguously attribute outcomes to one facility and make our patient sample more homogeneous. This produces a sample of about 5.3 million patients over 12 years. We are most interested in the effect on mortality, which is an unambiguously bad outcome, has little measurement error, and is difficult to “game” on the part of a facility or a government agency. For these and other reasons, short-term mortality (with suitable risk adjustment) has become the gold-standard measure of provider quality in the health economics and policy literature (McClellan and Staiger, 1999; Hull, 2018). We use an indicator for death within 90 days following discharge, including deaths that occur in the nursing home. There is a high level of short-term mortality—one in six patients die within three months of discharge—indicating the general morbidity of this patient cohort.

We use two measures of spending: the amount billed to Medicare for the patient stay, and the amount for the stay plus the following 90 days, in case better quality care leads to lower subsequent spending (both in 2016 dollars). Medicare covers all costs until the 21^{st} day of stay, when the patient begins paying a coinsurance. About 90% of total payments in our data are from Medicare, with patients bearing the remainder. We complement the mortality analysis with three ancillary measures of patient well-being, which CMS uses when computing the Five Star quality ratings for nursing homes. The first is an indicator for the patient's self-reported mobility score declining during the stay. The second is an indicator for developing a pressure ulcer. The third is an indicator for the patient's self-reported pain intensity score increasing during the stay.

To identify nursing homes acquired in PE deals, we make use of a proprietary list of transactions in the "elder and disabled care" sector compiled by Pitchbook Inc., a leading market intelligence firm in this space. The deals span 2004 to 2015, so that we will have sufficient time to evaluate outcomes. We match the target names to individual nursing facilities using name (facility or corporate owner) and address as recorded in the CMS data. This process yields 128 deals, which correspond to a change in ownership to PE for 1,674 facilities. The vast majority of deals in Pitchbook are not at hazard of matching, as they concern assisted living or other elder care companies that are not Medicare-accepting skilled nursing facilities. (See Appendix A for details.)

Figure C.1 shows the number of deals by year. We observe about 90 unique PE firms that acquired nursing homes. Most deals are syndicated and involve multiple PE firms. Table C.1 presents the top 5 deals by number of facilities acquired. Deal sizes are skewed, with the top 5 deals accounting more than half of the facilities acquired. On average, we observe PE-owned facilities for eight years post-acquisition, so the results should be interpreted as medium to long-term effects of PE ownership. While we likely underestimate PE's presence in this sector, our sample size is similar to an estimate of 1,876 nursing homes reportedly acquired by PE firms over a similar duration, 1998–2008 (GAO, 2010). The PE investors in our sample include very large funds, smaller funds, and specialized healthcare PE investment funds. PE firms which account for the most deals include The Carlyle Group and Formation Capital.

3.2 Descriptive Statistics

Overall, PE investment in healthcare has increased dramatically in recent decades, as shown using Pitchbook data in Panel A of Figure 1. Panel B focuses on the Elder and Disabled Care sub-sector, which includes the nursing homes that we study as well as assisted living and other types of care. The shaded areas in the graphs correspond to years after our sample ends, and indicate that deal activity continued to accelerate beyond 2015. The bottom two panels describe the skilled nursing facilities in our CMS data that are PE-owned. As of 2015, PE-owned facilities represented about 9% of all nursing facilities in the data, corresponding to an annual flow of about 100,000 patients. Note that the large spike in the mid-2000s seen in all the graphs reflects an economy-wide PE boom during this period, and is not specific to healthcare. Similarly, the flat lining in Panels C and D starting in 2010 reflects the lull in deal activity due to the Great Recession. Given the patterns in Panel B, the share of facilities that are PE-owned is likely substantially higher today.

Table 1 Panel A presents summary statistics on key variables observed at the facility-year level, where a facility is a single nursing home. Panel B presents summary statistics at the unique patient level on the final Medicare patient sample (recall we focus on a patient's first stay). PE targets are slightly larger, have fewer staff hours per resident, and a lower Overall Five Star rating. At the sector level, ratings and staffing have secularly increased over time. For staffing, this reflects more stringent regulatory standards. As the PE deals occur later in the sample on average, it is remarkable that they have lower average ratings. Panel B shows that demographic measures are similar across the types of facilities, such as patient age and a high-risk indicator.[10] PE-owned facilities bill about 10% more per stay than non-PE facilities. Appendix Figure C.2 panel A presents the CDF of stay lengths for Medicare patients in our sample. Medicare stays are relatively short—the median stay is 25 days, and the 90^{th} percentile is less than 80 days. We limit the sample to stays less than 100 days long because Medicare does not pay for longer stays.

[10] We use the Charlson Comorbidity Index, a standard measure of patient mortality risk based on co-morbidities. We create a high-risk indicator that is equal to one if the previous-year Charlson score is greater than two.

We describe which characteristics are associated with buyouts in Table A.1. Facilities in more urban counties and in states with higher elderly population shares are more likely to be targeted.[11] County-level percent black does not predict buyouts, nor do income and home-ownership (not presented). Chain-owned facilities are more likely to be acquired than independent facilities, likely reflecting the fixed costs of a PE deal. A higher share of Medicare patients (the omitted group) is positively associated with being targeted. Finally, the Five Star overall rating has a negative relationship with buyouts, indicating that PE firms target relatively low-performing nursing homes. These factors remain statistically significant predictors when included simultaneously in the same model, shown in column 5. These results highlight the need to estimate the effects of PE ownership within-facility.

4 Empirical Strategy for Patient-Level Analysis

There are two primary concerns related to measuring the causal effects of PE ownership on patient-level outcomes. First, PE funds may target facilities that are different in ways the econometrician cannot observe. To partly address this concern, we include facility fixed effects, eliminating time-invariant differences across facilities. We also include market-by-year fixed effects, identifying PE effects off of variation among patients in the same market and in the same year. This common design does not fully account for unobservables driving PE targeting. Therefore, we focus our causality argument on treatment effects for the treated, rather than external validity to a random firm in the economy. Our evidence indicates that treated firms were not on track to the outcomes we observe and would have continued, at least in the medium term, on their pre-existing path in the absence of the LBO. This interpretation is important for social welfare as private equity expands its footprint in the economy; even if we suspect that target firms "need" LBOs because they are underperforming or under-leveraged (or both), our results raise questions about the social planner trading off patient well-being against firm value.

The second concern is that following a PE buyout, the composition of patients may

[11] The map in Figure C.3 shows that deals are not excessively concentrated in particular areas of the country.

change, further confounding the analysis. Differential customer selection following PE ownership could reflect both supply-side channels such as changes in advertising and hospital referrals, or patient perceptions about PE ownership. Recent studies have documented that nursing homes selectively admit less costly patients (Gandhi, 2020). Hackmann et al. (2018) find that patients with cognitive impairments and who need help with more activities of daily living (ADL) are the most expensive to serve. Further, CMS payment adjustment emphasized rehabilitation therapy, which favors healthier patients who can tolerate therapy (Carter et al., 2012; Castelluci, 2019).[12] Our empirical analysis seeks to first understand whether compositional changes do occur and then introduces an instrumental variables approach to address it.

For patient-level OLS analyses, we use the following differences-in-differences model, which exploits variation in the timing of the PE deals across facilities:

$$Y_{i,j,r,t} = \alpha_j + \alpha_{r,t} + \phi PE_{i,j,r,t} + X'_{i,z}\gamma + \varepsilon_{i,j,r,t}, \tag{1}$$

Here, $PE_{i,j,r,t}$ is an indicator set to one if patient i in Hospital Referral Region (HRR), r, chooses PE-owned facility j in year t. Our preferred model controls for facility, α_j, and patient HRR by year fixed effects, $\alpha_{r,t}$. We flexibly allow markets to evolve on different trends to mitigate the possibility of differences in market structure confounding the results. The vector $X_{i,z}$ denotes patient risk controls including age, indicators for gender, marital status, dual eligible, and 17 disease categories.[13] Standard errors are clustered by facility to account for unobserved correlation in outcomes across patients treated at the same nursing home. We assess robustness to the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) estimators.[14]

[12]Medicare's payment adjustments were heavily tied to additional minutes of physical therapy until 2019. Unlike prospective payment for hospitals, there was no provision for outlier payments for the most expensive patients. For more details on payment adjustment, see https://www.cms.gov/Research-Statistics-Data-and-Systems/Computer-Data-and-Systems/MDS20SWSpecs/Downloads/44-Group-Worksheet.pdf. Carter et al. (2012) notes this approach created incentives for additional therapy and against admitting clinically complex patients.

[13]We construct these indicators with diagnosis codes recorded in claims from the three months prior to the index nursing home stay (hospital stays, ED visits, and outpatient visits).

[14]The former compares the outcomes of treated facilities with never-treated facilities, to ensure that using ever-

Consistent with the existing literature cited above, we show that patient risk declines following PE ownership. Table 2 Panel A presents point estimates for patient risk measures. Specifically, we test for changes in *initial* patient risk (assessed at the time of admission) following acquisition. We examine effects on a mix of co-morbidities to broadly capture changes in patient risk. The coefficients indicate that admitted patients are less likely to suffer from cognitive impairments (depression, dementia, Alzheimers) and need help with fewer ADLs following PE ownership, factors which strongly predict treatment costs. Figure 2 presents the corresponding event study plots, which generally suggest flat or increasing trends in patient risk prior to the deal but declining trends following the acquisition. We are concerned that this shift toward a healthier patient composition will lead to downward bias in mortality and spending effects. Therefore, we develop an instrument for the match between patients and nursing homes.

4.1 Distance-based Instrument

We combine the differences-in-differences model above with a differential distance instrument (McClellan et al., 1994) to control for endogenous patient selection into nursing homes. The thought experiment we approximate is to randomly draw a patient who goes to a PE facility after the buyout relative to a randomly drawn patient who went to that facility before the buyout, and then compare this difference to an analogous one in the same set of years for patients at non-PE facilities. The instrument to simulate randomly drawing patients exploits patient preference for healthcare providers located nearby (Einav et al., 2016; Card et al., 2019; Currie and Slusky, 2020). This is especially true for nursing homes; for example, Hackmann (2019) finds that the median distance between a senior's residence and her nursing home is under 4.3 miles. In our data, the median and 90^{th} percentile distances between a patient and her nursing home are 4.6 and 18 miles, respectively. About 35% of all patients choose the facility located closest to them (see Figure C.4).[15] As a result of these patterns, this instrument has been used to control for

treated facilities as controls does not bias the results. The latter corrects for treatment effect heterogeneity by re-weighting observations according to the share of facilities that are treated in each year.

[15]Distance patterns remain remarkably stable over time in our sample. Mean distance to facility is unaffected by PE buyout, as shown in Figure C.4D.

patient selection into nursing homes (Grabowski et al., 2013; Huang and Bowblis, 2019).

The differential distance instrument is the difference (in miles) between two distances: from a patient's home zip code to the closest PE-owned facility zip code; and from the patient's residence to the nearest non-PE facility zip code. Lower values of the instrument mean the patient is relatively closer to a PE-owned facility. When it is negative, the nearest PE-owned facility is closer than the nearest non-PE-owned facility. PE ownership evolves over time as more deals take place (and some PE funds exit their investments), creating variation across years in differential distance for individuals residing in the same zip code. Following convention, we drop patients facing a large differential distance value, specifically, one of more than 20 miles.[16] This also has two benefits: First, included patients plausibly live in markets targeted by PE firms and are thus more homogeneous; Second, the instrument has more power because it excludes inframarginal patients in places where facility choice is not sensitive to differential distance.

We estimate the first and second stages using Equations (2) and (3), respectively. The endogenous regressor of interest $PE_{i,j,r,t}$ is, as above, an indicator set to one if patient i in Hospital Referral Region (HRR), r, chooses PE-owned facility j in year t. We instrument with linear and squared differential distance, D_i, applicable to patient i based on her zip code, z, in the year the stay begins, t.

$$PE_{i,j,r,t} = \alpha_j + \alpha_{r,t} + \zeta_1 D_i + \zeta_2 D_i^2 + X'_{i,z}\xi + \nu_{i,j,r,t}, \tag{2}$$

$$Y_{i,j,r,t} = \alpha_j + \alpha_{r,t} + \phi \hat{PE}_{i,j,r,t} + X'_{i,z}\gamma + \varepsilon_{i,j,r,t}, \tag{3}$$

The other variables are as described for Equation (1). It is crucial to include facility fixed effects here (α_j) in order to control for level characteristics that attract PE ownership but are not caused by it. Our setting departs from that in McClellan et al. (1994), the canonical paper that used differential distance, because they study the causal effect of using a particular clinical

[16]We exclude zip codes based on the absolute magnitude of the differential distance, treating patients very close to PE facilities the same as those very far away. In practice very few zip codes are more than 20 miles closer to a PE facility. Differential distance values update for some zip codes over time as facilities are acquired or sold by PE firms. We exclude such zip codes only if their differential distance remains more than 20 miles in magnitude throughout.

procedure rather than the facility-level attribute of ownership.

The instrument is strongly predictive of nursing home type. The first stage results are reported in Table 3. Column 2 presents the estimates from our preferred specification. A five mile decrease in differential distance (0.4 s.d.) increases the probability of going to a PE-owned nursing home by 2.7 percentage points (pp), a quarter of the mean. The F-statistic exceeds 200, well above conventional rule-of-thumb thresholds for weak instruments.[17] We conduct multiple robustness checks, which include adding time-varying socioeconomic variables at the patient's zipcode-year level (z) and omitting all controls.[18]

IV estimation differs from randomized controlled trials because it requires two untestable assumptions. The first is conditional random assignment, under which unobserved characteristics correlated with the outcomes of interest are not correlated with differential distance after conditioning on covariates. This subsumes the exclusion restriction, which is that the patient's differential distance to a PE facility affects outcomes only by influencing her probability of being treated at a PE facility.

To test for conditional randomization, we examine the correlation between the instrument and patient observables, particularly covariates which may affect mortality, such as risk. Figure 3 Panel A presents the relationship between patient risk and the instrument and indicates little or no correlation.[19] The figure shows that the probability of being a high-risk patient (Charlson score > 2) increases by 0.1% for a 10 mile increase in differential distance. This is small in absolute terms and negligible compared to the proportion of high risk patients in the sample: 27%. Table 3 columns 1 and 2 show that the coefficients on differential distance are nearly unaffected by including patient-level controls, corroborating this interpretation. One important

[17]An alternative approach to constructing differential distance is to consider distance from the hospital where the patient was treated prior to the nursing home stay, rather than her residence. However, this has found to be a weaker instrument (Rahman et al., 2016; Cornell et al., 2019).

[18]The socioeconomic variables, from the American Community Survey, are annual median household income, the share of the population that are white, that are renters rather than home-owners, and that are below the Federal poverty line. In unreported analyses, we find similar results if we use a linear model in differential distance rather than quadratic.

[19]We project the high-risk indicator (see Section A.2) on the controls we use in our main regression, and collapse the residuals into ten bins. Similarly, we run a regression of differential distance on the controls and collapse the residuals into ten bins. We plot the means of each bin, with the risk residuals on the Y-axis and distance residuals on the X-axis. The figure also presents a fitted line and the slope coefficient.

test adds time-varying zip code-level socioeconomic controls in case PE firms target places on track to different demographic profiles (Table 3 column 3). We also confirm that the coefficients are robust to using a much more granular market definition, to mitigate the concern of within-market targeting of patients (Table 3 column 4).[20]

Under random assignment, characteristics of patients with above- and below-median differential distance should be similar. Table 4, where we summarize patient characteristics for the two groups, suggests this is the case. The top two rows of the table show that, consistent with a strong instrument, the probability of going to a PE-owned facility declines from 19% for below-median group to 3% for the above-median group. The patient characteristics in the subsequent rows are extremely similar between the two groups. For example, 64% of patients in each group are women. The instrument also appears to balance patients on the same measures of cognitive impairments and activities of daily living that decline post-buyout. Appendix B describes evidence on random assignment in more detail. For example, one test in the spirit of Angrist et al. (2010) and Grennan et al. (2018) shows that differential distance lacks predictive power for inframarginal patients, in the first stage and in outcome equations.

The second assumption is monotonicity, under which lower differential distance makes all patients more likely to choose a PE-owned facility. This is true on average, but the assumption is at the patient-level which is untestable. Monotonicity is necessary to interpret the IV estimate as a well-defined local average treatment effect (LATE). Figure 3 Panel B contains a binscatter plot of the first stage, showing that the likelihood of going to a PE-owned facility increases nearly linearly with differential distance. It is estimated in the same way as Panel A described above, except that the outcome is an indicator for the facility being PE-owned. The linear pattern is consistent with monotonicity. Appendix B describes further evidence supporting this assumption.

[20]We use Hospital Service Areas (HSAs) as an alternate, more granular definition of nursing home markets. There are nearly 3,400 HSAs in the US, while there are only about 300 HRRs. Both HRRs and HSAs were defined by the Dartmouth Atlas group based on healthcare use patterns by Medicare beneficiaries so that they are relatively self-contained.

5 Patient-Level Effects

This section presents the main results of the paper, which are the effects of PE ownership on short-term mortality and spending per patient. It then considers observed and unobserved heterogeneity in these effects. Finally, it examines measures of patient well-being.

5.1 Effects on Mortality and Spending

We begin with OLS models using Equation (1), which includes patient-level controls, facility fixed effects, and patient HRR-by-year fixed effects. The results are in Table 2 Panel B. We find an OLS effect on mortality of 0.3 pp, which is 2% of the mean. There are small, negative effects on spending of 1-2% (columns 2-3). We expect that the selection on unobservedly lower risk should bias these OLS results down, as discussed in Section 4 and indicated by the risk measures in Figure 2. The corresponding event studies, in Figure C.6, suggest no pre-trends, supporting the parallel trends assumption that underlies our empirical model (i.e., target facilities and control facilities would continue on parallel trends absent the buyout).[21]

The IV effects using Equation (3) are reported in Table 2 Panel C. Consistent with downward bias in OLS, we see much larger effects in IV analysis. However, it is important to emphasize that the IV effects are for compliers with the instrument who go to the closest nursing home, and thus could experience larger effects than a randomly selected patient. Column 1 shows that going to a PE-owned nursing home increases the probability of death during the stay and the following 90 days by 2.4 pp, or 13% of the mean. In the context of the health economics literature, this is a very large effect. Next, the amount billed per nursing home stay per patient—which is almost all paid by Medicare—increases by 10% (column 2). As Table 1 shows, on average PE-owned nursing homes bill $13,400 per stay, while non-PE nursing homes bill $12,400. Higher costs do not seem to reflect additional preventive care that enables lower costs later, because the total amount billed for the stay and the subsequent 90 days increases by 8.5%. The IV estimates imply that the reduced form effects should decline

[21] These figures are constructed by collapsing data to the facility-year level and estimating an event study version of Equation (1).

as differential distance grows larger (i.e., relative to the nearest alternative, a PE facility is farther away). Figure 4 provides non-parametric evidence of such a pattern, using the same approach as in Figure 3 except that the y-axis variables are the patient outcomes. Consistent with the IV results, mortality and spending are highest among patients with the lowest differential distance and decline as patients are relatively further away from PE facilities.

We calculate the implied cost in statistical value of life-years in Table C.3 Panel C. The IV coefficients are mapped to lives and life-years lost using the number of index stays at PE-owned nursing homes during our sample period. This calculation implies that 27,951 additional deaths occurred due to PE ownership over the twelve-year sample period. To estimate life-years lost, we rely on observed survival rates for Medicare patients at all nursing homes. This leads to an estimate of about 214,000 lost life-years.[22] Applying a standard estimate of statistical value of a life-year of $100,000 (Cutler and McClellan, 2001) inflated to 2016 dollars, we arrive at a mortality cost of $27.8 billion.

We present a range of robustness tests in Appendix B, and summarize the most important ones here. First, we use a placebo analysis to assess whether pre-existing trends might explain the results. We artificially set the PE dummy to turn on before the deal and drop observations after the true deal. Table 2 Panel D finds small and insignificant placebo effects, consistent with no differential trends prior to acquisition. Table 5 row 2 reports specification checks that vary the controls and market definition. Importantly, we expect that that if the instrument does not randomly assign patient risk, patient controls should substantially affect the results. In row 2.A, we omit all patient controls. In row 2.B., we include zip-year socioeconomic controls.[23] Across all of the tests, the coefficients remain robust and similar in magnitude to the main estimates

[22]As life expectancy differs substantially between men and women, we estimate the effect separately by gender. We calculate the average life expectancy at discharge by gender by observing the actual life span for each patient in our data. For patients still alive at the end of our sample period, we approximate the year of death based on patient gender and age using Social Security actuarial tables. We adjust this downward to account for the fact that decedents tend to be older on average (by about 2 years). We then applied this mean life expectancy to the number of deaths computed above and obtained the number of life-years lost. This approach may overstate the true value if the *incremental* deaths at PE facilities are of older patients. This approach also understates the true value since we don't account for the loss in longevity not resulting in death.

[23]The other tests are as follows. In row 2.C, we use more granular HSAs instead of HRRs to define patient markets. In row 3, we limit the patient sample using a stricter differential distance threshold of 10 miles instead of 20 miles. In row 4, we use an indicator for above-median differential distance rather than the continuously value. In row 5, we cluster standard errors by deal rather than by facility.

in row 1. Appendix B presents other checks that validate the instrument, such as showing that it is very weak among patients who are relatively very far or very close to PE-owned facilities and does not explain mortality for these patient groups (Table C.4). Finally, we present the alternative OLS Callaway and Sant'Anna (2021) and Sun and Abraham (2021) estimators in Figure C.5 Panel A.

The effect on mortality is robust to alternative durations. Table C.5 shows that the effect is similar to the main result as a percent of the mean for horizons from 15 to 365 days. For example, the effect is 13% when mortality is measured at 30 days following discharge, and 11% at 365 days.

The results so far point to nuanced effects of PE ownership. Since patients become less risky after PE buyouts, there may be either cream-skimming on the part of the facility or changes in how patients select the nursing home. We find a very large IV effect on mortality and a small OLS effect, consistent with the OLS capturing some compositional shifts towards less risky patients. The IV result represents a causal effect within the subset of patients who comply with the instrument by going to the closest facility; these patients may be more vulnerable, in the sense that they do not opt to travel farther to find the best match, and may face more information frictions. In this subset, we find a very large, positive effect on mortality. We discuss the IV effects further below in a marginal treatment effects analysis.

Alternative Explanations

An alternative interpretation of these results is that PE ownership could bring economies of scale or corporatization, which Eliason et al. (2020) propose to explain the negative effects of dialysis center mergers. To test this hypothesis, we conduct two tests in Table 5. The first adds to our main model a control for being a chain versus an independent facility (about 15% of PE owned facilities remain independent post-buyout). If our effects are explained by the "rolling-up" of independent facilities into more efficient chains, the estimates should attenuate. Instead, they are essentially unchanged (row 6.A). Second, we use only the top five deals to define PE ownership. In these deals, the target chains already owned more than 100 facilities and stayed nearly the same size over the sample period. Therefore, in this model chain size is held constant and we evaluate the effect of a change in ownership. The effects remain large and significant (row 6.B). In sum, it does not seem that chain corporate structures or synergies in large firms explain our results.

We test whether our results are driven by select large deals or PE firms. The estimates remain large and significant if we exclude facilities bought as part of the top 2 deals, each involving more than 300 facilities (row 7.A). Similarly, the results are robust to excluding facilities bought by Formation Capital and Filmore Capital, which may not be representative of the average PE firm given their specialization in nursing homes (row 7.B). We also show that the results are robust to excluding nonprofit nursing homes, which account for about 20% of patients (row 8).

Finally, it is possible that PE firms also acquire hospitals and influence the decision to send patients to nursing homes, since most patients in our sample enter the nursing home immediately after a hospital stay. To assess this concern we examine how PE entry into a market affects hospital discharges to nursing homes. Table C.6 Panel A presents OLS estimates of patient-level models in which the outcome is probability of being discharged to a nursing home. Using markets defined at both the HRR and HSA levels, PE entry into a market does not appear to change hospital referral decisions on the extensive margin.

5.2 Heterogeneity in the IV Mortality Effect

The selection on risk we document above raises the question of whether the effects are larger for some groups than for others. This section explores heterogeneity both on observed attributes and on unobserved resistance to treatment, using a Marginal Treatment Effects (MTE) framework.

Observed attributes

To assess heterogeneity in the IV analysis, we split the sample based on observed characteristics in Table 6. We also report the mean mortality rates for each sub-group to help interpret the magnitudes. First, higher risk as measured by disease burden should be associated with more need for high-skill, medicalized RN care. Lower risk patients might be more sensitive to changes in staff attentiveness (for example helping them to use the toilet or minimizing infection risk). Therefore, we split the sample into two groups around the high-risk indicator (Charlson score above two), which isolates patients with higher mortality (29% vs. 14%). The results indicate that relative to the mean mortality rate, lower risk patients experience a much greater increase in mortality (0.026/0.14 $\approx$ 19% vs. 0.02/0.29 $\approx$ 7%, row 1).

We consider gender in row 2 and find similar effects among men and women. Third, we divide the sample at the median length of stay. Note that length of stay could be affected by PE ownership, so this analysis should be thought of as relevant to understanding the mechanism. The mortality effect is driven by patients with below median stays, consistent with the previous result that lower risk patients experience worse mortality effects. It also contradicts a potential concern that PE facilities appear worse on mortality because of sicker patients who require long stays and are independently more likely to die.

We explore this further by studying the impact of PE ownership on length of stay at different parts of the length of stay distribution. We estimate a series of IV regressions (using Equation (2)) in which we adjust the dependent variable to be an indicator for the stay being longer than X days. Figure C.2 panel B presents the estimated effects. We plot the X values on the x-axis and the coefficient from the model is plotted on the y-axis. For example, the coefficient on $x = 20$ days implies a 5 pp increase in the probability of stays becoming longer than 20 days following PE ownership. The figure documents that PE-owned facilities keep very short stayers longer, with little or no effect on stays becoming longer than 35 or more days. This would maximize Medicare revenue, because Medicare pays fully for only the first 20 days of care and then then tapers off. Tying this to the mortality results above, it may be that extending short stays plays an important role in elevating mortality.[24]

[24]We also find an increase in length of stay only for low-risk patients (results not reported). Since we found the mortality effect was driven by low-risk patients, this further lends support to the interpretation that extending length of stay is linked to elevated mortality.

Table 6 row 4 examines mortality effects for patients discharged to different destinations. The mortality effect is driven by patients discharged to facilities (predominantly hospitals), though the coefficients are positive for all destinations. Note that we do not find changes in the proportion of patients sent to the different destinations (see Table C.6 panel B). However, there could be changes in the composition of patients sent to different locations. In row 5 we disaggregate patients discharged to hospitals by the category of the reason for hospitalization, and find the largest effect on mortality occurs for patients with an injury or infection, which may be consistent with lower quality care.

MTE Theory and Estimation

We can begin to reconcile the smaller OLS and larger IV results using a marginal treatment effects (MTE) analysis. Unlike the LATE, the MTE seeks to estimate parameters that are not specific to the complier group and allow us to make more general statements regarding the causal effects of PE ownership within the treated sample of facilities. The IV LATE may mask treatment effect heterogeneity across different types of patients and ignores the possibility of patient selection on treatment gains. The MTE framework allows us to examine these dimensions and compute parameters such as the Average Treatment Effect (ATE) and Average Treatment on the Treated (ATT) (Heckman and Vytlacil, 2005; Heckman et al., 2006).

We denote $Y_{0,i}$ and $Y_{1,i}$ as potential outcomes for individual i in the untreated ($k = 0$) and treated ($k = 1$) states, respectively. Treatment in our setting is receiving care at a PE-owned facility, PE_i. We model these potential outcomes $Y_{k,i}$ as a function of observed control vector X_i and dummies for facility, F_j and market-year interactions, $R_{r,t}$. $U_{k,i}$ denotes all unobserved factors.[25]

$$Y_{k,i} = X_i'\beta_k + F_j + R_{r,t} + U_{k,i}, \quad k = 0, 1 \tag{4}$$

We then propose a latent selection model of how patients choose a PE-owned facility based on

[25] Following Brinch et al. (2017), we assume that the error term $U_{k,i}$ is normalized to be conditional mean zero, i.e., $\mathbb{E}[U|X = x, F = f, R = r] = 0$.

observed and unobserved factors:

$$\begin{aligned} PE_i^* &= Z_i'\delta - V_i, \\ PE_i &= 1 \; if \; PE_i^* \geq 0, \; PE_i = 0 \quad \text{otherwise}, \end{aligned} \tag{5}$$

where $Z = (X, F, R, D, D^2)$ is a vector including all the controls listed above in Equation (4) and the differential distance instruments excluded from the outcome equation, D_i and D_i^2. We interpret V_i as the unobserved resistance to going to a PE-owned facility. This selection model imposes monotonicity by using a constant parameter δ for all individuals. Following the MTE literature, we transform the selection equation into the quantiles of the distribution of V rather than its absolute values:

$$Z_i'\delta - V_i \geq 0 \implies Z_i'\delta \geq V_i \implies \Phi(Z_i'\delta) \geq \Phi(V_i), \tag{6}$$

where Φ is the cumulative distribution function of V_i. We interpret $\Phi(Z_i'\delta)$ as the propensity score, the probability that an individual with observed characteristics Z_i chooses a PE nursing home, and denote it as $P(Z)$. $\Phi(V_i)$ represents the quantiles of unobserved resistance to treatment, and is denoted as U_D.

Omitting subscripts for simplicity, define $MTE(X = x, U_D = u) = \mathbb{E}[Y_1 - Y_0 | X = x, U_D = u]$. The MTE is the treatment gain for an individual with characteristics $X = x$, who is in the u^{th} quantile of the resistance distribution. Such individuals are indifferent to receiving treatment when their propensity score $P(Z)$ equals u. Following the convention in the recent MTE literature (Brinch et al., 2017; Cornelissen et al., 2018), we assume that the MTE is additively separable into observed and unobserved components. Therefore, it is identified over the unconditional support of $P(Z)$ for all values of X rather than the support of $P(Z)$ conditional on $X = x$, easing the burden of identifying variation:

$$\begin{aligned} MTE(X = x, U_D = u) &= \mathbb{E}[Y_1 - Y_0 | X = x, U_D = u] \\ &= \underbrace{x(\beta_1 - \beta_0)}_{observed} \quad + \quad \underbrace{\mathbb{E}[U_1 - U_0 | U_D = u]}_{unobserved}, \end{aligned} \tag{7}$$

This assumption also implies that treatment effect heterogeneity from X affects the MTE curve in u only through the intercept, so the slope of the MTE curve in u does not depend on X. The potential outcomes model described above produces the following outcome equation as a function of observables and $P(Z)$ (Carneiro et al., 2011).

$$\mathbb{E}[Y|X, F, R, P(Z) = p] = X'\beta_0 + F + R + X'(\beta_1 - \beta_0)p + K(p), \tag{8}$$

where $K(p)$ is a nonlinear function of the propensity score. The derivative of this outcome equation with respect to p estimates the marginal treatment effect at $X = x$ and $U_D = p$ (Heckman et al., 2006).

We estimate the selection model under linear probability in Equation (5) and obtain $\hat{p} = Z'\hat{\delta}$. Figure 5 Panel A presents the variation in the estimated propensity score. We collapse the data to percentiles of differential distance, D and plot a non-parametric fit of $P(Z)$ values against the corresponding percentile means of D. This shows a similar pattern first observed in Figure 3—the probability of going to a PE-owned facility declines nearly monotonically as differential distance increases. However, this figure masks the full support of the distribution of $P(Z)$, which extends over the entire unit interval. Figure 5 Panel B highlights the overlap in distribution of the propensity scores for treated and untreated patients by plotting histograms for the two groups against $P(Z)$ on the X-axis. The figure confirms that the treated and untreated groups overlap in distributions over nearly the entire unit interval.[26] We then estimate the outcome Equation (9) below, assuming $K(p)$ is a polynomial in p of degree S.

$$Y = X'\beta_0 + F + R + X'(\beta_1 - \beta_0)\hat{p} + \sum_{s=2}^{S} \rho_s K(\hat{p}) + \epsilon. \tag{9}$$

The MTE curve is the derivative of Equation (9) with respect to $\hat{p}$. In our baseline model we set $S = 2$, but show robustness to higher order polynomials. Standard errors are obtained by block bootstrap, clustering by facility.

[26] We have at least 50 patients from both the treated and control groups at every percentile value of the propensity score over the range 0-0.94. We trim the sample to this range when estimating the MTE curve.

5.2.1 MTE Results

We estimate Equation (9) and confirm the presence of selection on unobserved resistance by testing the joint significance of the coefficients ρ_s on the higher order terms of the polynomial in p (Heckman et al., 2006). The coefficient on p^2 is highly statistically significant (p value < 0.01), confirming patient selection into PE facilities on unobserved resistance.

Figure 5 Panel C presents the MTE curve and its 90% confidence intervals. We use a second degree polynomial, so the MTE curve is linear in unobserved resistance (u). Its downward slope implies reverse selection on treatment gains; that is, individuals with the least resistance to going to a PE facility experience the worst mortality effects. In contrast, individuals with the highest resistance experience negative (i.e., beneficial) effects. The figure also plots the ATE, which is 0.9 pp (s.e. 1.2 pp).[27] We aggregate the MTEs using the appropriate weights, shown in Figure 5 Panel D, to obtain various treatment effect parameters (Cornelissen et al., 2016). Given the downward sloping nature of the MTE curve, we expect the ATT to be higher than the ATUT. Indeed, we estimate an ATT of 3.3 pp (s.e. 0.8 pp) and an ATUT of 0.5 pp (1.2 pp). Only the ATT is statistically significant among the three treatment effect parameters.

In sum, the ATE implies that a randomly chosen Medicare patient from our sample would experience a 0.9 pp increase in the chance of short-term mortality if she goes to a PE-owned nursing home. This is in between the 0.3 pp OLS effect and the 2.4 pp IV LATE. It implies a large number of deaths in a counterfactual where all Medicare short-stay patients receive care at a PE-owned facility. Second, the MTE curve implies reverse selection on gains and that some patients – those with greater resistance to treatment – experience improvements in mortality if they choose a PE-owned facility, though the negative MTE values are not statistically significant.

[27] Figure C.7 panel A shows a specification check on the assumption of a linear MTE curve. We compute a weighted average MTE equivalent to the main 2SLS estimate and obtain a similar value (2.3 pp vs. 2.4 pp), suggesting little mis-specification error. We also estimate the MTE curve using higher order polynomials. Figure C.7 Panel B shows that the curve remains downward sloping regardless of the polynomial.

5.3 Patient Well-Being

If the effect on short-term mortality is related to lower patient welfare, we expect to see consistent evidence using other wellbeing measures. We focus on three clinical measures of wellbeing that CMS uses as outcomes for short-stays when computing Five Star ratings (surprisingly, mortality is not one of them). These are patient mobility, developing ulcers, and increasing paint intensity. The OLS models find positive effects on all three outcomes, reported in Table 7 Panel A. Relative to their respective means, there is a decrease in mobility of 6.2% (column 1), increase in ulcer development of 10% (column 2), and increase in pain intensity of 9% (column 3). The corresponding event studies, in Figure C.6, indicate no differential pre-trends and large, gradual increases following acquisition.

The IV models, in Panel B of Table 7, show positive effects on two of the three outcomes. Mobility decreases by 4% of the mean (column 1), while pain increases by 12% of the mean (column 3). However, there is no effect on developing ulcers in the IV model (column 2). Overall, the evidence of harmful effects on other measures of patient wellbeing help confirm that the adverse effect on mortality is not a spurious finding.

6 Operational Changes

This section uses facility-level data to explore operational changes that could help explain the adverse patient welfare effects described above.

6.1 Empirical Strategy

For outcomes available only at the nursing home level, we cannot instrument for patient selection so we use a facility-level version of the OLS differences-in-differences model, presented in Equation (10).

$$Y_{j,t} = \alpha_j + \alpha_t + \beta PE_{j,t} + P'_{j,t}\gamma_1 + M'_{j,t}\gamma_2 + \varepsilon_{j,t} \tag{10}$$

$PE_{j,t}$ takes a value of one if facility j is PE-owned in year t. The coefficient of interest is β, which captures the relationship between PE ownership and the outcome $Y_{j,t}$. We include facility (α_j) and year fixed effects (α_t). We retain all facilities in our preferred specification, but the results are robust to limiting the sample to for-profit facilities. The vector $P_{j,t}$ includes three controls for facility-level patient mix and $M_{j,t}$ includes five county-level controls for time-varying market attributes.[28] As there may be concern that control variables could be affected by PE ownership, we also present results without any controls.

The identifying assumption is that PE targets and control facilities would continue on parallel trends in the absence of the acquisition. We test for differential pre-trends using event study figures, which plot the coefficients β_s from Equation (11).

$$Y_{j,t} = \alpha_j + \alpha_t + \sum_{s \neq 0} \beta_s \text{Deal Year}_{\text{j,s}} + P'_{j,t}\gamma_1 + M'_{j,t}\gamma_2 + \varepsilon_{j,t} \tag{11}$$

$\text{Deal Year}_{\text{j,s}}$ is an indicator that is one in year s relative to the buyout year for facility j, and zero otherwise. The remaining terms are as defined above for Equation (10). Finally, as above, we show robustness to the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) estimators for these facility-level models.

6.2 Results

We consider three types of operational channels. The first two explicitly concern facility quality, while the last pertains to financial strategies particular to the PE industry. All the results are presented in Table 8. For each outcome, the top row of coefficients are from specifications with only facility and year fixed effects, while the bottom row adds the full set of patient and market controls. Event studies are in Figures 6 and 7.

[28]Patient mix controls: Case Mix Index (CMI) is a composite measure of patient risk based on medical history of diagnosis or treatment for a large number of conditions. Second, Acuity index is a measure of patient risk computed using the patient's assessed Activities of Daily Living (ADL) scores. In both cases, a greater value indicates a riskier patient cohort for the nursing home. We winsorize both the CMI and Acuity Index at the 1% and 99% level in each year. The third control is the share of the facility's patients who are Black. County-level controls: Herfindahl Hirschman Index (HHI) based on shares of beds, number of for-profits, number of chain-owned, number of hospital-based, and number of overall facilities. These are calculated using a leave-one-out procedure from the facility-level data.

6.2.1 Compliance With Standards and Staff Availability

First, we consider compliance with care protocols in Panel A of Table 8. Our outcome of interest is the facility-level Five Star rating, which varies from one (worst) to five (best). After PE buyouts, the Deficiency rating declines by 0.08 points (column 1), which is about 3% of the mean and 7% of the standard deviation (the most relevant measure given how this variable is constructed). This rating reflects whether the facility is satisfying care protocols such as storing and labeling drugs properly, disinfecting surfaces, as well as other aspects of care such as ensuring resident rights and avoiding patient abuse. The Overall rating similarly declines (column 2). Figure 6 presents event studies for each outcome. There are no pre-trends, consistent with the identifying assumption, and the negative effects appear immediately after the change in ownership and persist for at least five years.[29]

Intensive subsidy is one reason high-powered profit maximizing incentives may lead to adverse effects in the nursing home context. While we cannot randomly allocate subsidy intensity across facilities, for these compliance outcomes we can assess whether facilities that rely more on Medicare for revenue experience more adverse effects. Indeed, Table C.7 shows that the negative effects on the two rating measures are driven by facilities with above-median Medicare revenue. For example, the negative effect on the Deficiency rating is -.118 for this group, or about 4.1% of the mean and 9.5% of a standard deviation.[30]

In Table 8 Panel B, we assess effects on nursing staff hours per patient-day, a well-established measure of nursing home quality that accounts for changes in patient volume. Column 1 shows a modest decline of 0.05 hours in aggregate staff hours (1.4% of the mean). This masks larger changes for different types of nurses that offset each other. There is a decrease in ‘front line’ caregivers (CNAs and LPNs), shown in columns 2 and 3, respectively.

[29]The Overall rating has three components: the Deficiency rating, a Quality rating based on metrics computed using claims data and clinical assessments, and a Staffing rating, which is based on staffing measures evaluated in Panel B. Since we assess quality and staffing changes more granularly, we do not present the effects on these components, but we find negative, significant effects of equal or larger magnitudes there as well.

[30]We restrict this analysis for these outcomes because they are facility-wide and do not depend on the type of patient, while the other splits (staff, mortality) reflect the composition of patients and the requirements of different payers. For example, Medicare patients require more RNs. In unreported analysis, we do not find differential effects in our other outcome measures.

Together there is a decline of around 0.09 hours for these two groups (3% of the mean). In contrast, there is an increase in use of Registered Nurses (RNs) by about 0.04 hours (8%). The event studies in Figure 6 again reveal no pre-trends and show immediate declines after the deal in front-line staffing, while the increase in RN staffing appears in the third year after the buyout. The increase in RN staff hours does not compensate for the decline in lower skilled nurse hours because RNs account for a small fraction of all staff hours. Medicare cost reports indicate that CNAs and LPNs receive an hourly wage that is about 40% and 70% respectively of the wage paid to RNs, which is around $35 per hour. Unfortunately, we cannot observe whether facilities take cost reduction steps such as using more part-time labor and reducing individual shifts.

We perform multiple robustness tests such as including controls for chains, excluding the top two deals, and including only for-profit nursing homes (Table C.8). The coefficients are similar. The alternative OLS Callaway and Sant'Anna (2021) and Sun and Abraham (2021) estimators are in Figure C.5 Panel B. Following Goodman-Bacon (2021), we also decompose the D-D estimate into the weight on treated facility timing relative to either always or never PE different components (Table C.9).

Using estimates from the literature for the effect of frontline nurse availability on mortality, we calculate that the estimated decline in frontline nurse staffing predicts an increase in mortality of 0.25 pp.[31] It is intuitive that lower staffing – in particular low-skill staffing – would be associated with increases in adverse conditions related to lack of attention, such as lower mobility and higher pain intensity. Higher RN availability is consistent with less complex patients driving the mortality effects. RNs are responsible for the medicalized aspects of care, while front line nurses support daily living activities such as preventing infections. Managers may have looked for ways to cut overall labor costs while changing the mix of nursing staff capability to maintain quality and patient experience, as RNs are crucial to

[31]Tong (2011) exploits an increase in minimum nurse staffing regulation in California and finds a decline in on-site patient mortality due to greater availability of frontline nurses. Specifically, Tong (2011) reports a 15% decline in mortality due to an increase in nurse availability of one hour per resident-day. Since we estimate a decline of 0.09 hours, this predicts an increase of 0.09 x 15 = 1.4% of the mean, or 0.24 pp. More recently, Ruffini (2020) exploits variation in minimum wage requirements to isolate the effects of nurse staffing changes on quality and also finds mortality effects.

nursing home quality (Zhang and Grabowski, 2004; Lin, 2014). An alternative explanation is the regulatory focus on RNs. For example, CMS uses the availability of RNs to determine eligibility for Medicare reimbursement.[32] Given the tight regulatory scrutiny of RN availability, it is difficult to reduce staffing levels in this category.

To explore the relationship between declines in staff availability and quality, we compare changes in staff availability and Five Star ratings within target facilities around the PE buyout event. This recovers correlations and does not imply causality, so we present the raw data in bin-scatter plots. Figure C.8 shows the change in Five Star rating over the three years around PE acquisition on the Y-axis against the change in aggregate staff hours per patient day during the same period on the X-axis. The plots show that facilities which experienced larger declines in staff availability also experienced greater declines in ratings. The patterns are consistent across rating types and suggest that cuts to nursing staff may be an important channel to explain the quality declines.

6.2.2 Finances and Operations

Our final analysis uses CMS cost reports to analyze key sources of expenditure related to the PE business model. We begin by noting that nursing homes are widely known to have relatively low and regulated profit margins, often cited at just 1-2%.[33] Our data on nursing home cost reports submitted to CMS indicate that nursing homes report negative operating margins on average, and PE-owned nursing homes are not on average more profitable. In unreported analysis, we see no effect of buyouts on net income or overall revenue or costs. This raises the question of how PE firms create value from nursing home investments.

There are three types of firm expenditures that the academic literature and popular press particularly associate with the PE playbook. The first is what are often termed “monitoring fees" charged to portfolio companies (in the CMS cost reports, these are listed as

[32] Specifically, such facilities are defined by having “an RN for 8 consecutive hours a day, 7 days a week (more than 40 hours a week), and that there be an RN designated as Director of Nursing on a full time basis.” See https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/Downloads/som107c07pdf.pdf.

[33] http://www.medpac.gov/docs/default-source/data-book/jun17_databookentirereport_sec.pdf

"management fees").[34] Metrick and Yasuda (2010) note that these are thought to be between 1-5% of EBITDA. Our data suggest that they increase over time after buyouts, as shown in Figure 7 Panel A, where the fees are flat before the buyout, and then rise dramatically afterwards. Table 8 Panel C column 1 indicates that on average, management fees increase by 7.7% after acquisition (we exponentiate large coefficients since the outcome is in log dollars).

The second type of expenditure is lease payments. The value of real estate is one reason that nursing homes and other typically low-margin assets can be profitable investments; the investor can sell the real estate to a related company or to a third party (Dixon, 2007; Keating and Whoriskey, 2018; Brown, 2019). Cash from the real estate sale can be disbursed as profits to the PE fund. A cash inflow early in the life of the investment is especially beneficial to the fund's Internal Rate of Return, a key industry performance metric. The nursing home assumes the obligation of future rent payments. As an example, a *New York Times* report on the nursing home industry notes that:

> "[PE] investors created new companies to hold the real estate assets because the buildings were more valuable than the businesses themselves, especially with fewer nursing homes being built. Sometimes, investors would buy a nursing home from an operator only to lease back the building and charge the operator hefty management and consulting fees" (Goldstein et al., 2020).[35]

Consistent with this strategy, column 2 shows that facility building lease payments increase dramatically by about 76% after PE acquisitions. Figure 7 Panel B confirms the lack of pre-trends and the increase post-buyout.

The third type of expenditure is interest on debt. While not a direct source of PE profits, debt is tightly related to the overall PE model for creating value. Metrick and Yasuda (2010) note

[34]In their summary of buyout fund economics, Metrick and Yasuda (2010) write that "we think of monitoring fees as just another way for BO funds to earn a revenue stream." These fees should not be confused with the usual 2% of fund value that General Partners earn each year for managing Limited Partners' capital, before profits from investments.

[35]Two examples further illuminate these types of transaction. First, the HCR Manorcare deal discussed in Section 2.2, where the chain's real estate assets were spun off and sold shortly after the acquisition by the Carlyle Group. Second, at a Congressional hearing the executive director of the Long-Term Care Community Coalition said "more and more with entities buying up nursing homes, they have no experience in the business, they sell out the underlying property" (Brown, 2019).

that the ratio of debt to equity in a buyout deal is typically around 5:1. The interest payments become a cost to the portfolio company. In Figure 7 Panel C, we see that like the previous two outcomes, interest payments are flat before the buyout and then rise dramatically afterwards. Column 3 indicates that the increase is about 225%.

Taking the results on nurse availability together with the estimated effects on interest, lease, and management fees payments, we infer that PE ownership shifts operating costs away from staffing towards costs that are profit drivers for the PE fund. To our knowledge, this paper offers the first instance in the literature on PE in which these three profit drivers have been documented systematically.

The final outcome we explore is patient capacity and volume. Table C.10 column 1 finds no measurable change in the number of beds, which may partly reflect state regulations restricting expansions. Admissions increase by 3.5%, or 6.5 patients per year for the average facility (column 2). The event study, in Figure C.9B, shows an increasing trend post-acquisition. The apparent disconnect between demand and quality of care may reflect information frictions in observing nursing home quality, as discussed earlier (Arrow, 1963; Grabowski and Town, 2011; Werner et al., 2012). Higher admissions raise the question of whether PE ownership increases overall access to nursing home care, providing care for individuals who would not otherwise have gone to a nursing home. To test whether this is the case, we assess the effects of PE entry into a nursing home market, using the HRR definition. Table C.10 column 3 shows that there is no effect of initial PE entry on admissions at the market level, corroborated by flat patterns in the event study (Figure C.9C). Hence, the increase in facility-level admissions likely reflects business stealing.

7 Conclusion

This paper studies PE buyouts in healthcare, an important sector where PE activity has increased and generated policy debate. Nursing homes are a useful setting because they have particularly high levels of for-profit ownership, intensive government subsidy, and have experienced extensive PE investments. In our analysis, we address both targeting and patient selection challenges to identification. We find that going to a PE-owned facility significantly increases short-term mortality. The amount depends on patient composition. OLS results suggest an effect of about 2%, while an IV approach suggests a much larger effect of 13% within the relatively vulnerable population that goes to the closest facility. A marginal treatment effects analysis helps to reconcile these results, finding that a randomly selected patient would experience a 5% increase in mortality chances because of going to a PE-owned nursing home. We document multiple changes in clinical and operational factors that help explain the increased mortality and spending. We also find a corresponding increase in operating costs that tend to drive profits for PE funds.

There are many channels for future research. Although our results imply that PE ownership reduces productivity in the nursing home context, it may well have positive effects in other healthcare sectors with better functioning markets. Beyond healthcare, there has been significant PE investment in sectors such as education, defense and infrastructure that also feature high levels of government subsidy and opaque product quality. Further work can help design government programs to align the interests of PE-owned firms with those of taxpayers and consumers.

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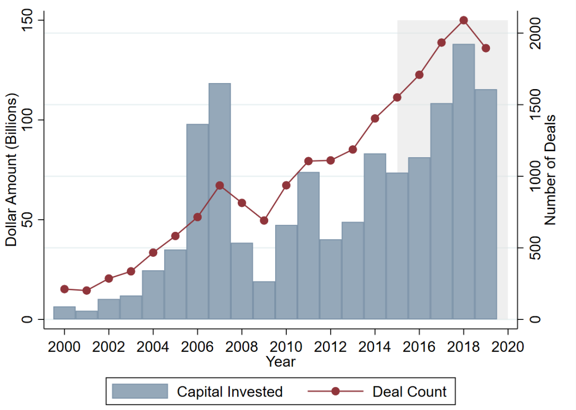
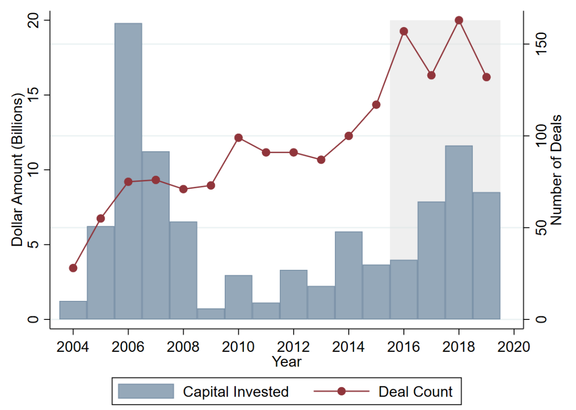
Figures and Tables

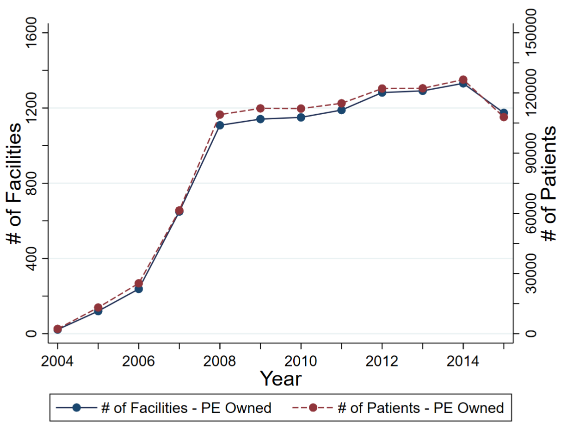
Figure 1: **Private Equity Ownership in Healthcare**



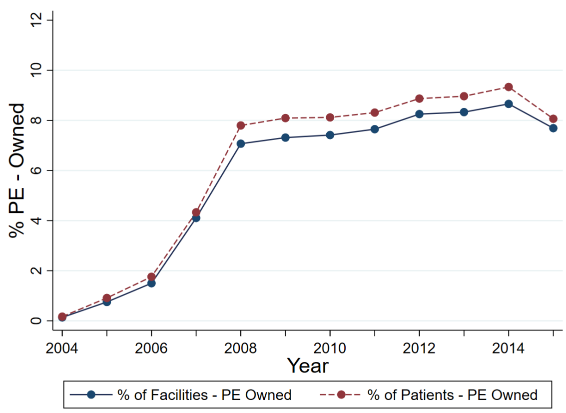
A: PE Deals in Healthcare



B: PE Deals in Eldercare



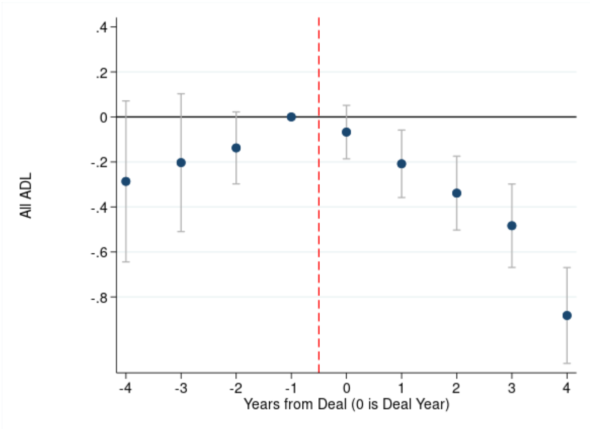
C: Number of Facilities and Patients Acquired



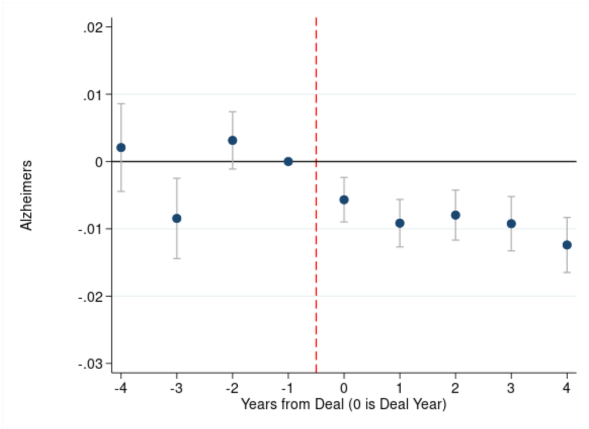
D: Percentage of Facilities and Patients Acquired

Note: This figure shows PE deals in health care over time. Panels A and B present the total capital invested (left axis) and number of transactions (right axis) by PE firms in healthcare and eldercare, by year. Panels C and D focus on the number of active nursing homes owned by PE firms in each year. Panel B presents the number of PE-owned facilities (left axis) and patients admitted at these facilities (right axis). Note that the total number of facilities ever bought by PE firms is larger (1,674) than what is plotted here since some of these facilities closed or went back to non PE ownership over time. Panel D presents these trends as a percentage of total number of facilities and patients admitted, respectively.

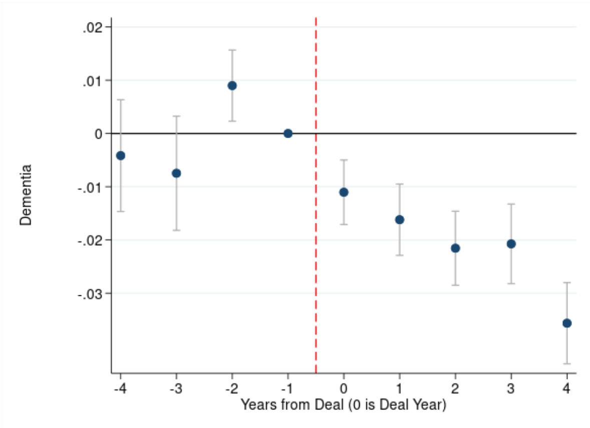
Figure 2: **Initial Patient Assessments**



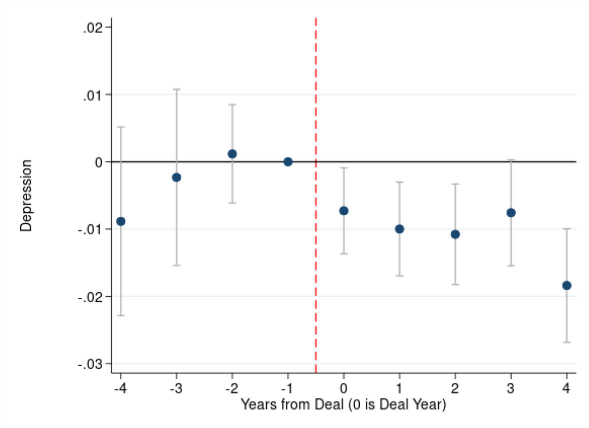
A: ADL Score



B: Alzheimers



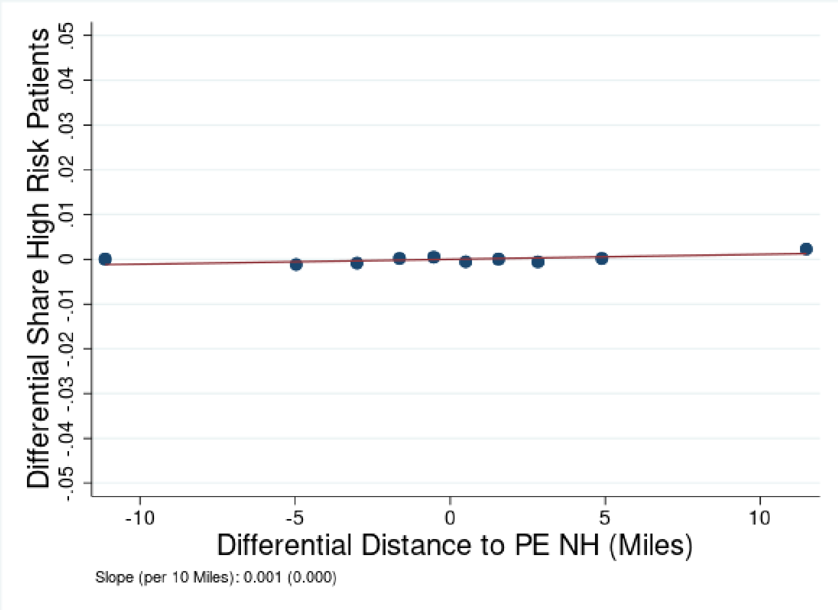
C: Dementia



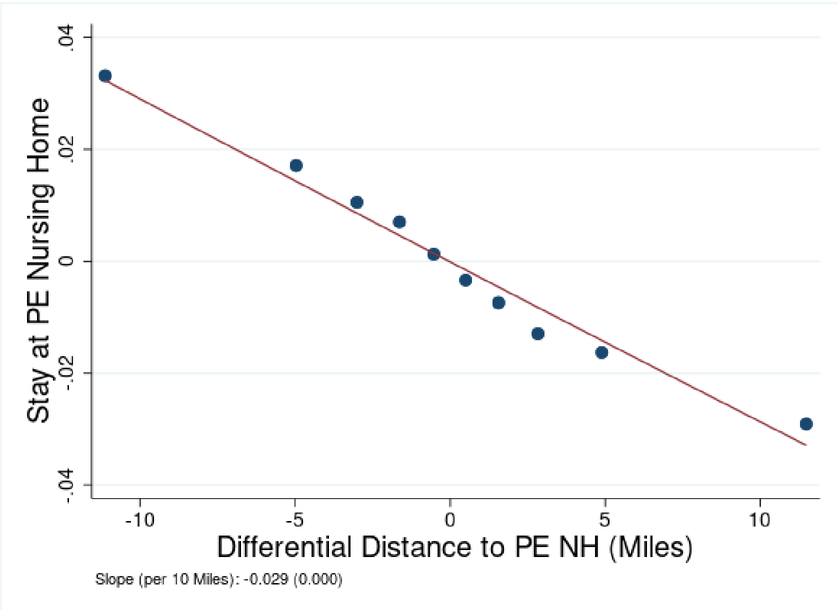
D: Depression

Note: This figure presents event studies on initial patient assessments around the time a nursing home experiences a PE buyout. We estimate these models on collapsed facility-year level data. Each point in the figures represents a coefficient obtained by estimating an event study version of Equation (1). Year = -1 is the omitted point. Panel A presents results on activities of daily living (ADL) score for patients where a higher score indicates more dependence, Panel B on an indicator for Alzheimers, Panel C on an indicator for Dementia, and Panel D on an indicator for Depression, respectively, at admission to the index nursing home stay. Standard errors are clustered by facility.

Figure 3: **Patient Characteristics with Differential Distance**



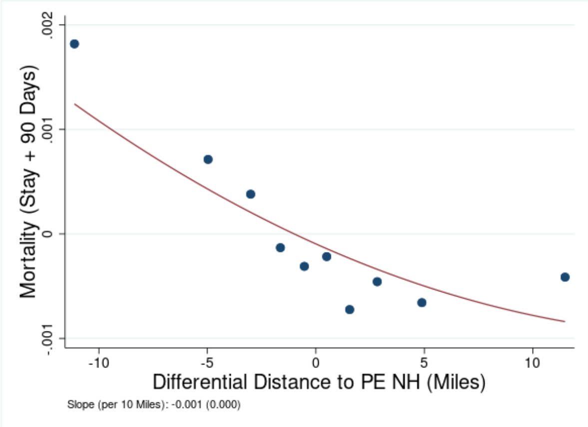
A: High Risk Patients



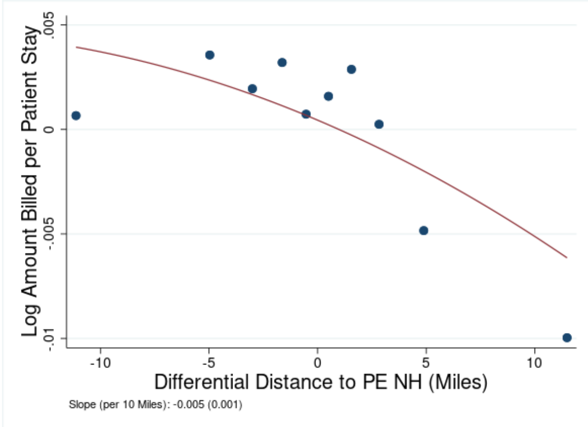
B: Stay at PE Nursing Home

Note: This figure presents scatter plots of patient characteristics against differential distance to the nearest PE facility. The independent variable is the difference in distance (in miles) of the nearest PE nursing home to the nearest non-PE nursing home for the patient. The dependent variable in Panel A is an indicator for the patient to have a Charlson Co-morbidity Index (based on diagnoses recorded in hospital inpatient and outpatient claims over the 3 months before admission to nursing home) greater than 2, and in Panel B is an indicator for the nursing home being PE-owned. The data was collapsed into 10 equal sized bins and we plot the means of residuals in each bin that were obtained from models including facility and patient HRR x Year fixed effects, and patient demographics: age, race, gender, maritial status, and an indicator if patient is dual eligible. Panel B additionally controls for indicators for 17 pre-existing conditions used to compute the Charlson Index. The figures also present quadratic fitted lines for these plots. Each plot also presents the slope coefficient (per 10 miles of differential distance) with the corresponding standard error. Standard errors are clustered by facility.

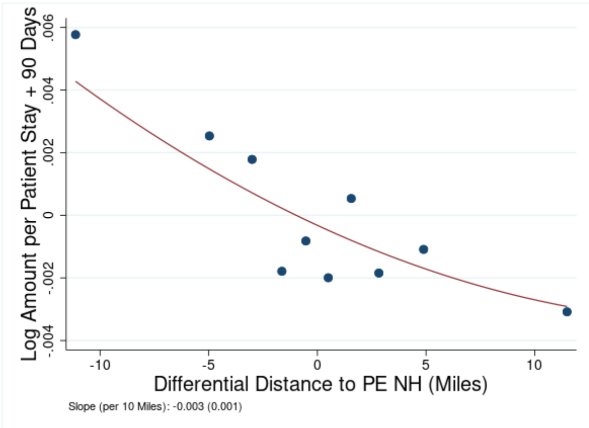
Figure 4: **Patient Outcomes with Differential Distance**



A: Mortality (Stay + 90 Days)



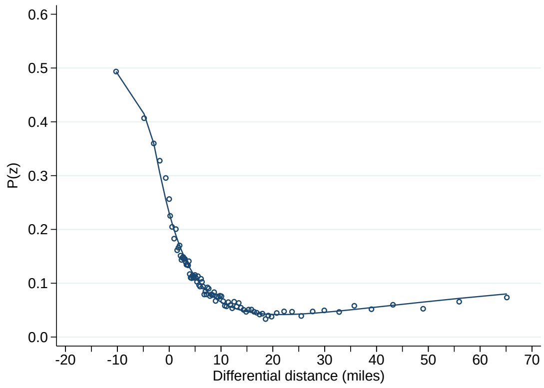
B: Log Amount Billed per Patient Stay



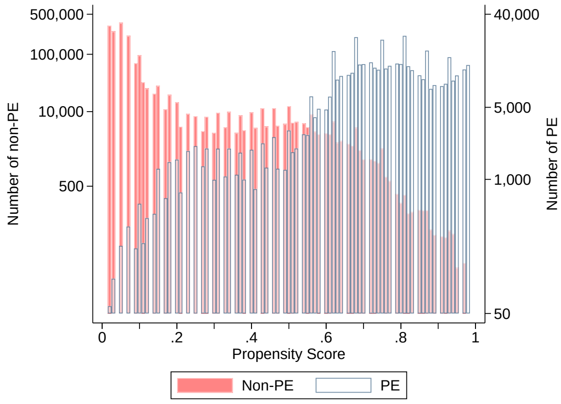
C: Log Amount Billed per Patient Stay + 90 Days

Note: This figure presents scatter plots of patient characteristics against differential distance to the nearest PE facility. The independent variable is the difference in distance (in miles) of the nearest PE nursing home to the nearest non-PE nursing home for the patient. The dependent variable in Panel A is an indicator for patient death during or 90 days post nursing home stay, in Panel B refers to log of the total payment for the index nursing home stay, and in Panel C is the log of the total payment for index stay and 90 days post nursing home stay. The data was collapsed into 10 equal sized bins and we plot the means of residuals in each bin that were obtained from models including facility and patient HRR x Year fixed effects, and patient demographics: age, race, gender, maritial status, indicators for 17 pre-existing conditions used to compute the Charlson Index, and an indicator if patient is dual eligible. The figures also present quadratic fitted lines for these plots. Each plot also presents the slope coefficient (per 10 miles of differential distance) with the corresponding standard error. Standard errors are clustered by facility.

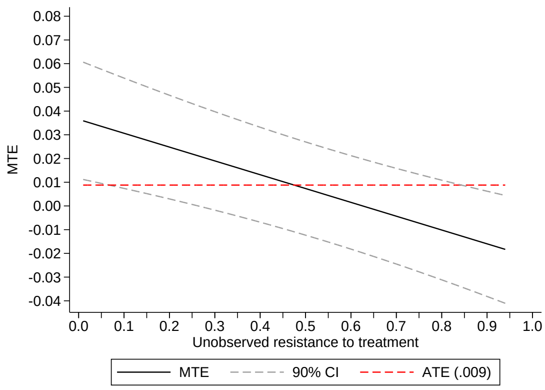
Figure 5: **Marginal Treatment Effects**



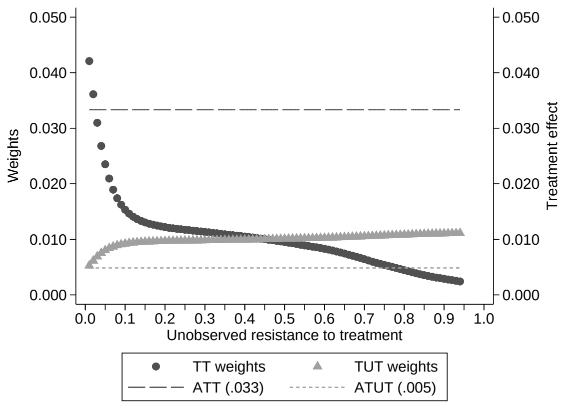
A: First stage



B: Common Support



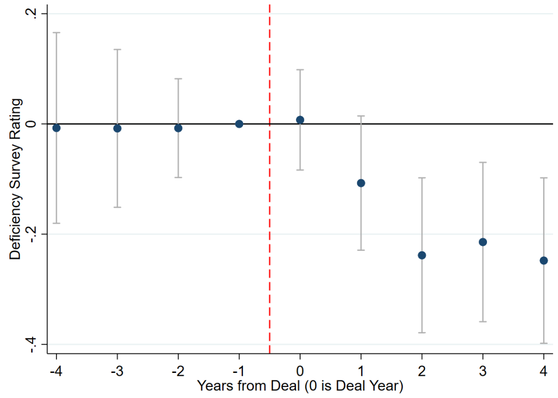
C: MTE curve



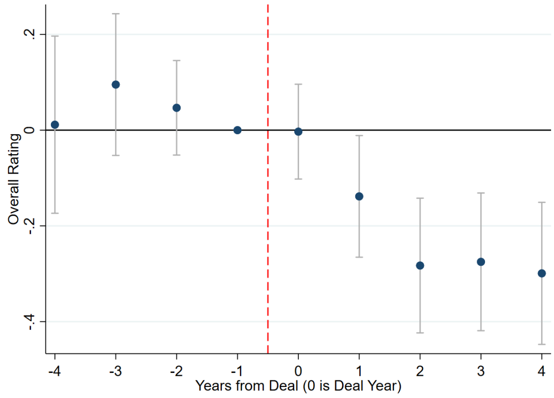
D: ATT and ATUT

Note: This figure presents results pertaining to Marginal Treatment Effects (MTE) analysis using the Medicare patient-level data. Panel A presents the 'first stage' fit of predicted probability of treatment or propensity score, w.r.t the instrument. Panel B presents the overlap in distributions of PE and non-PE groups by propensity score. This plot uses a log scale due to the large number of non-PE patients with low propensity. Panel C presents the weights for the IV and corresponding estimates. Panel D presents the weights for the Average Treatment on the Treated (ATT) and Average Treatment on the Untreated (ATUT) and the corresponding estimates. Section 5.2 presents details of the MTE estimation.

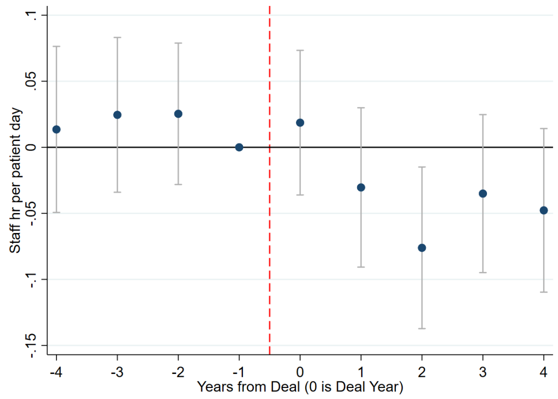
Figure 6: **Aggregate Quality and Staffing Outcomes**



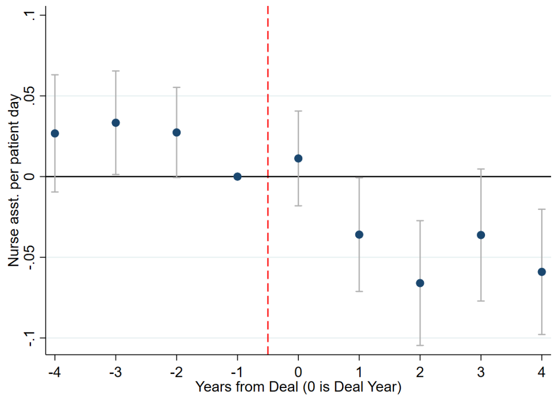
A: Deficiency Survey Rating



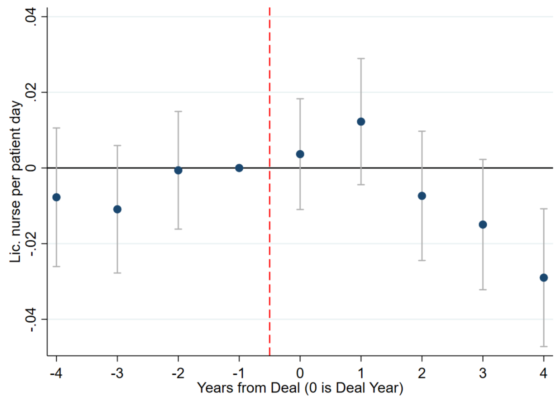
B: Overall Rating



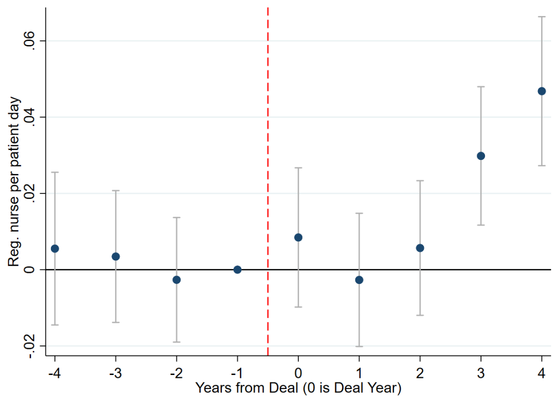
C: Staff Hour per Patient Day



D: Nurse Asst. per Patient Day



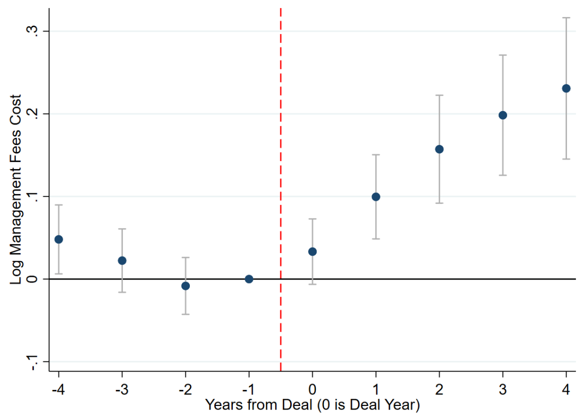
E: Lic. Nurse per Patient Day



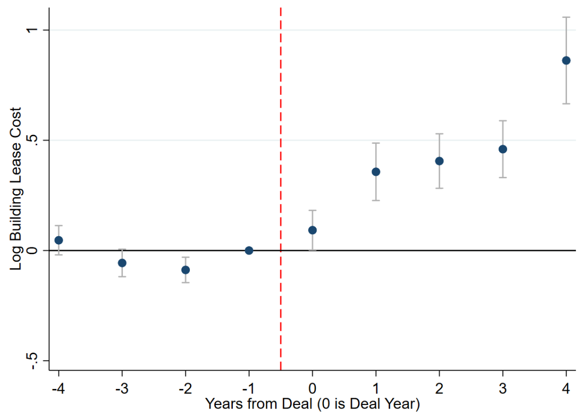
F: Registered Nurse per Patient Day

Note: This figure presents event studies on quality of care measures (Five Star ratings) and Staffing around the time a nursing home experiences a PE buyout. Each point in the figures represents the coefficient β_s obtained by estimating Equation (11) as discussed in Section 6. Year = -1 is the omitted point. In Panels A and B, we present effects on the Five-star ratings awarded by CMS - deficiencies identified by independent contractors in audits and overall rating, respectively. A negative effect on ratings implies a decline in quality. Panels C to F present results on nurse staffing per-patient for all staff, nurse assistants, licensed nurses, and registered nurses respectively. All models include facility and year fixed effects, patient mix and market controls, as described in Section 6.1. All dependent variables are winsorized at 1 and 99% level. Standard errors are clustered by facility.

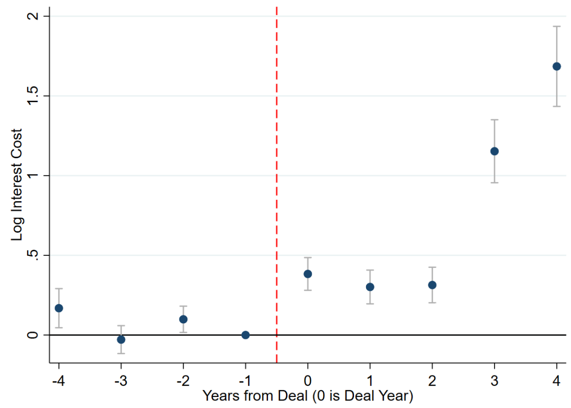
Figure 7: **Facility Finances**



A: Log Management Fee Cost



B: Log Building Lease Cost



C: Log Interest Cost

Note: This figure presents event studies on facility finances around the time a nursing home experiences a PE buyout. Each point in the figures represents the coefficient β_s obtained by estimating Equation (11) as discussed in Section 6. Year = -1 is the omitted point. Panels A to C present results on the log of management fee cost, building lease cost, and interest cost, respectively. All models include facility and year fixed effects, patient mix and market controls, as described in Section 6.1. All dependent variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Table 1: **Descriptive Statistics**

	All			Not PE Owned		PE Owned	
	Mean	SD	Count	Mean	Count	Mean	Count
A. Facility Level Attributes							
Overall Five-Star Rating	3.17	1.30	138,204	3.20	127,441	2.83	10,763
Deficiency Five-Star Rating	2.84	1.25	138,204	2.86	127,441	2.62	10,763
Staff Hours per Pat. Day	3.59	1.49	284,108	3.60	271,118	3.38	12,990
Nurse Assistant Hours per Pat. Day	2.28	0.79	284,108	2.29	271,118	2.06	12,990
Licensed Nurse Hours per Pat. Day	0.82	0.46	284,108	0.82	271,118	0.82	12,990
Registered Nurse Hours per Pat. Day	0.46	0.57	284,108	0.46	271,118	0.49	12,990
Number of Beds	104.48	56.60	284,108	104.11	271,118	112.34	12,990
Admissions	184.16	166.97	284,108	180.40	271,118	262.47	12,990
Ratio Black	0.10	0.17	284,108	0.10	271,118	0.12	12,990
Ratio Medicaid	0.60	0.24	284,104	0.60	271,114	0.60	12,990
Ratio Medicare	0.15	0.17	284,104	0.15	271,114	0.18	12,990
Ratio Private	0.25	0.19	284,104	0.25	271,114	0.22	12,990
Management Fees (2016$)	7,076	120,673	231,795	6,001	219,231	25,833	12,564
Building Lease (2016$)	5,860	80,223	231,826	4,825	219,262	23,919	12,564
Interest Expense (2016$)	12,911	163,562	231,855	5,588	219,291	140,733	12,564
B. Medicare Patient Attributes							
Age	81.28	8.07	5,305,193	81.34	4,715,657	80.81	589,536
Female	0.64	0.48	5,305,193	0.64	4,715,657	0.62	589,536
Black	0.08	0.28	5,305,193	0.08	4,715,657	0.09	589,536
White	0.88	0.33	5,305,193	0.88	4,715,657	0.88	589,536
Married	0.35	0.48	5,305,193	0.35	4,715,657	0.36	589,536
Charlson Score (Previous) > 2	0.27	0.44	5,305,193	0.27	4,715,657	0.29	589,536
Cardio-Vascular Disease	0.18	0.39	5,305,193	0.18	4,715,657	0.18	589,536
Injury	0.19	0.39	5,305,193	0.19	4,715,657	0.19	589,536
Other	0.63	0.48	5,305,193	0.63	4,715,657	0.63	589,536
Dual Eligible	0.16	0.36	5,305,193	0.16	4,715,657	0.15	589,536
Differential Distance (Miles)	9.93	12.57	5,305,193	10.95	4,715,657	1.75	589,536
Mortality (Stay + 90 Days)	0.18	0.38	5,305,193	0.18	4,715,657	0.19	589,536
Uses Anti-Pyschotics	0.09	0.28	5,305,193	0.09	4,715,657	0.09	589,536
Mobility Reduces	0.53	0.50	5,305,193	0.52	4,715,657	0.62	589,536
Develops Ulcers	0.08	0.27	5,305,193	0.08	4,715,657	0.09	589,536
Pain Intensity Increases	0.27	0.44	5,305,193	0.26	4,715,657	0.30	589,536
Amount Billed per Patient Stay (2016$)	12,500	11,000	5,305,193	12,400	4,715,657	13,400	589,536
Amount Billed per Patient Stay + 90 Days (2016$)	19,900	19,700	5,305,193	19,800	4,715,657	21,100	589,536

Note: This table presents descriptive statistics for key variables used in the analysis. Panel A presents descriptives on facility-level data for all nursing homes over the years 2000–17 while Panel B presents patient-level data for Medicare patients with index stays over the years 2005–16. A unit of observation is a facility-year in Panel A and a unique patient in Panel B (since we retain only the first stay per patient). Columns 1, 2 and 3 present means, standard deviations and number of observations for the full sample. We categorize facilities into two groups. Columns 4 and 5 present means and number of observations at facilities that never experienced a PE acquisition or before PE acquisition during our sample period. Columns 6 and 7 present corresponding values for facilities in the post-buyout period. For most variables, about 10% of the observations pertain to facilities that experienced a PE acquisition. Sample sizes differ across variables in Panel A since they were sourced from multiple sources or in some cases were reported only for more recent years. In Panel A, all continuously varying variables were winsorized at the 1% and 99% levels. We compute the Charlson Co-morbidity Index using co-morbidities diagnosed in hospital inpatient and outpatient claims (first 10 dx codes) over the 3 months prior to, but not including, the index stay. Spending values in Panel B are winsorized at the 99% level and deflated to be in 2016 dollars. 'Total' billing includes hospital inpatient, outpatient including emergency department, and nursing home stay spending over the 90 days following discharge from the index stay and includes the index stay. The following patient-level variables were sourced from the Minimum Data Set (MDS): marriage, mobility, pressure ulcers, and pain intensity. Medicare patients that could not be merged into the MDS (94% match rate) were dropped from the sample. Facilities with less than 100 Medicare patients over the entire period were omitted from the patient-level sample. If any of the MDS variables was missing, then we set the respective indicator to zero. We exclude patients facing an absolute magnitude of differential distance of greater than 20 miles.

Table 2: **Effect of Private Equity Buyouts on Patient Outcomes**

	A: Initial Patient Assessments (OLS Estimates)			
	(1) ADL Score At Admission	(2) Alzheimers At Admission	(3) Dementia At Admission	(4) Depression At Admission
1(PE)	-0.1077*	-0.0055***	-0.0161***	-0.0053**
	(0.061)	(0.001)	(0.002)	(0.002)
Observations	4,944,015	4,944,015	4,944,015	4,932,391
Y-Mean	15.62	0.05	0.16	0.25

	B: OLS Estimates		
	(1) Mortality (Stay + 90 Days)	(2) Log Amount Billed Per Patient Stay	(3) Log Amount Billed Per Patient Stay + 90 Days
1(PE)	0.0032**	-0.0264***	-0.0167***
	(0.001)	(0.006)	(0.005)
Observations	5,305,056	5,305,056	5,305,056
Y-Mean	0.18	9.00	9.51

	C: IV Estimates		
	(1) Mortality (Stay + 90 Days)	(2) Log Amount Billed Per Patient Stay	(3) Log Amount Billed Per Patient Stay + 90 Days
1(PE)	0.0241***	0.0970***	0.0806***
	(0.008)	(0.027)	(0.024)
Observations	5,305,056	5,305,056	5,305,056
Y-Mean	0.18	9.00	9.51
F-Stat	224	224	224

	D: Placebo Analysis (IV Estimates)		
	(1) Mortality (Stay + 90 Days)	(2) Log Amount Billed Per Patient Stay	(3) Log Amount Billed Per Patient Stay + 90 Days
1(PE)	0.0012	-0.0168	-0.0163
	(0.004)	(0.017)	(0.015)
Observations	4,872,544	4,872,544	4,872,544
Y-Mean	0.19	8.96	9.47
F-Stat	510	510	510

Note: This table presents estimates of the relationship between PE ownership and patient health and spending. Panel A presents OLS results for initial assessments of patients entering nursing homes, obtained by estimating Equation (1). In Panel B, each cell presents the coefficient β obtained by estimating Equation (1). The independent variable is an indicator for the patient being admitted to a PE nursing home. We present effects for claims-based patient quality outcomes - patient death within 90 days of discharge from the index stay, and total amount billed (2016$). Panel C presents the coefficient β for the same outcomes obtained by estimating Equation (3) by 2SLS, with the indicator for the patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest PE and non-PE facility. Panel D presents these results from a placebo analysis of the relationship between private equity ownership and patient health and spending. We assign placebo PE acquisition to three years before the actual acquisition and discard data for any facility starting with the year it actually got acquired. Accordingly we re-compute differential distance values taking into account these placebo acquisitions. All regressions include facility and patient HRR x Year fixed effects, and patient risk controls. Patient risk controls include age, race, gender, marital status, indicators for 17 pre-existing conditions used to compute the Charlson Index, and an indicator if patients are dual eligible. Standard errors are clustered by facility.

Table 3: **Patient-Level Analysis: First Stage**

	(1) 1(PE)	(2) 1(PE)	(3) 1(PE)	(4) 1(PE)
Differential Distance	-0.0580***	-0.0580***	-0.0578***	-0.0381***
(In 10 Miles)	(0.003)	(0.003)	(0.003)	(0.002)
(Differential Distance)^2	0.0077***	0.0077***	0.0076***	0.0057***
(In 10 Miles)	(0.001)	(0.001)	(0.001)	(0.000)
Facility FEs	Y	Y	Y	Y
Patient Controls		Y	Y	Y
Zipcode Controls			Y	
Patient FEs Level	HRR x Year	HRR x Year	HRR x Year	HSA x Year
Observations	5,305,056	5,305,056	5,298,289	5,304,378
Y-Mean	0.11	0.11	0.11	0.11
F-Stat	224	224	222	213

Note: This table presents estimates of the relationship between PE ownership of the nursing home and the patient's differential distance. Each cell presents the coefficient β obtained by estimating Equation (2). The independent variable is the difference in distance (both linear and quadratic, in 10 miles) to the nearest PE nursing home and the nearest non-PE nursing home for the patient. This is calculated based on distances between the respective zip code centroids. The outcome variable is an indicator for whether the nursing home serving the patient is PE-owned (=1 if PE-owned, 0 otherwise). Column 1 controls for facility and patient market (Hospital Referral Region) x Year fixed effects. Column 2 (our preferred specification) adds controls for patient risk controls (indicators for 17 pre-existing conditions used to define the Charlson Co-morbidity Index inferred from claims over the three months prior to admission, and sex, age, race, marital status, and an indicator if patients are dual eligible). Column 3 adds controls for patient zip-year characteristics: median household income, the shares of the population that are white, that are renters rather than home-owners, that are below the Federal poverty line, and that are enrolled in the medicare advantage program. Column 4 uses the same controls as in column 2 but defines patient market using a narrower market definition: Hospital Service Area (HSA) instead of HRR. Standard errors are clustered by facility.

Table 4: **Balance of Patient Characteristics**

Patient Attribute	(1) DD < Median	(2) DD > Median
Differential Distance	1.72	18.14
PE Owned Nursing Home	0.19	0.03
Age	81.27	81.30
Female	0.64	0.64
Black	0.09	0.08
Married	0.35	0.34
Charlson score categories:		
AMI	0.08	0.08
Congestive Heart Failure	0.22	0.24
PVD	0.05	0.05
CEVD	0.13	0.13
Dementia	0.04	0.04
COPD	0.21	0.23
Rheumatoid Arthritis	0.03	0.03
Peptic Ulcer	0.02	0.02
Mild Liver Disease	0.01	0.01
Diabetes	0.21	0.21
Diabetes + Complication	0.04	0.04
Paraplegia	0.03	0.03
Renal Disease	0.14	0.13
Cancer	0.09	0.09
Severe Liver Disease	0.01	0.01
Metastatic Cancer	0.04	0.04
AIDS	0.00	0.00
Initial Assessments:		
ADL Score	15.68	15.60
Alzhiemers	0.05	0.05
Dementia	0.16	0.16
Depression	0.25	0.25
Number Of Patients	2,652,840	2,652,353

Note: This table presents the balance in patient attributes with respect to the instrument: differential distance. We divide patients into two groups based on whether their differential distance is below or above the median value (8.9 miles). Recall that differential distance (DD) is the difference between distance to the nearest PE nursing home and the nearest non-PE nursing home for the patient. Column 1 presents the means of patient characteristics for patients with DD below the median value, while Column 2 presents the means for patients with DD greater than the median. We present patient demographics, 17 co-morbidity indicators used to compute the Charlson Co-morbidity Index, and 4 initial assessment characteristics of patients at the time of admission to the index nursing home stay from the Minimum Data Set. Charlson score categories were coded using diagnosis codes on hospital inpatient and outpatient claims over the 3 months prior to, but not including, the index nursing home stay. Paraplegia includes both partial and complete paralysis. We generated indicators for the Charlson score disease categories using the 'charlson' command in Stata, available at http://fmwww.bc.edu/RePEc/bocode/c/charlson.html.

Table 5: **Patient-Level Analysis: Robustness**

	(1) Mortality (Stay + 90 Days)	(2) Log Amount Billed Per Patient Stay	(3) Log Amount Billed Per Patient Stay + 90 Days
1. Base Specification			
1(PE)	0.0241***	0.0970***	0.0806***
	(0.008)	(0.027)	(0.024)
2. Varying Controls			
A. No Controls			
1(PE)	0.0320***	0.1429***	0.0836***
	(0.008)	(0.029)	(0.024)
B. Zip-Year Controls			
1(PE)	0.0233***	0.0964***	0.0797***
	(0.008)	(0.027)	(0.024)
C. HSA-Year FEs			
1(PE)	0.0457***	0.1417***	0.1646***
	(0.015)	(0.045)	(0.041)
3. Narrower distance threshold			
1(PE)	0.0178**	0.0514*	0.0494**
	(0.008)	(0.029)	(0.025)
4. Alternate functional form			
1(PE)	0.0371***	0.1671***	0.1190***
	(0.011)	(0.036)	(0.031)
5. Clustering by Deals			
1(PE)	0.0241**	0.0970***	0.0805**
	(0.011)	(0.035)	(0.035)
6. Corporatization			
A. Include Chain Controls			
1(PE)	0.0241***	0.0971***	0.0806***
	(0.008)	(0.027)	(0.024)
B. Top 5 Deals Only			
1(PE)	0.0490***	0.1353***	0.1200***
	(0.013)	(0.044)	(0.039)
7. Excluding select deals			
A. W/O Top 2 Deals			
1(PE)	0.0402***	0.1381***	0.1277***
	(0.012)	(0.042)	(0.037)
B. W/O Formation & Fillmore Capital			
1(PE)	0.0513***	0.1497***	0.1664***
	(0.014)	(0.050)	(0.044)
8. Only For Profits			
1(PE)	0.0195***	0.0769***	0.0604***
	(0.007)	(0.025)	(0.021)
Observations	5,305,056	5,305,056	5,305,056
Y-Mean	0.18	9.00	9.51

Note: This table presents results from specification checks on the relationship between PE ownership and patient health and spending, corresponding to results in Panel A in Table 2. The first panel presents the base specification. The second panel presents results by varying controls: row 2A presents coefficients from a model with fixed effects only, row 2B includes patient zip controls: median household income, the shares of the population that are white, that are renters rather than home-owners, that are below the federal poverty level, and that are enrolled in Medicare Advantage program, and while all other rows include HRR x year fixed effects, and row 2C uses Hospital Service Areas (HSA) instead of HRR. The third panel excludes all patients whose zipcode has a minimum differential distance of more than 10 miles. The fourth row uses an indicator of differential distance greater than median value rather than actual differential distance for the estimates. The fifth panel clusters estimates by deals instead of facilities. The sixth panel checks if results are driven by PE ownership or corporatization: row 6A controls for facility being part of a chain, and row 6B limits the PE group to only the facilities bought in the 5 largest PE deals. The seventh panel presents various sample cuts: row 7A calculates the results excluding all data for chains involved in the 2 largest PE deals, and row 7B excludes all deals with Formation and Fillmore Capital. The eight panel limits the sample only to for-profit facilities. All rows (except 2A) includes patient risk controls: age, race, gender, marital status, indicators for 17 pre-existing conditions used to compute the Charlson score, and an indicator if patients are dual eligible. Standard errors are clustered by facility (except for fifth panel).

Table 6: **Heterogeneity in Patient Mortality**

	(1) Observations	(2) Mean	(3) Coefficient	(4) (Std. Errors)
1. Risk				
Low Risk	3,874,419	0.14	0.0263***	(0.009)
High Risk	1,430,247	0.29	0.0203	(0.015)
2. Gender				
Male	1,911,713	0.22	0.0251*	(0.013)
Female	3,392,983	0.15	0.0229***	(0.009)
3. Length of Stay				
Length of Stay < Median	2,657,352	0.21	0.0414***	(0.012)
Length of Stay > Median	2,647,356	0.14	0.0135	(0.009)
4. Discharge Location				
Home	3,104,995	0.06	0.0085	(0.007)
Facility	1,331,943	0.34	0.0872***	(0.019)
Other	867,288	0.34	0.0082	(0.018)
5. Health Diagnosis for Discharge to Facility				
Injury and Infection	247,965	0.46	0.1221***	(0.045)
Cardio-Vascular	358,851	0.44	0.0491	(0.035)
Other	389,574	0.41	0.0874***	(0.033)

Note: This table presents heterogeneity in the effects of PE ownership on patient mortality. Column 1 presents the sample size and Column 2 presents the mean. Columns 3 and 4 present the corresponding coefficient β and its standard error obtained by estimating Equation (3) by 2SLS. The independent variable is the indicator for a patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest non-PE and PE nursing home. The outcome variable is an indicator for patient death within 90 days of discharge from the index stay. We explore heterogeneity on several patient level factors - by dividing patients into 2 groups based on severity of pre-existing co-morbidities (high risk = Charlson Index greater than 2) in row 1, gender in row 2, length of stay (above and below median) in row 3, and patient discharge location in row 4, and reason for discharge to facility in row 5. All models include facility and patient HRR x year fixed effects. We additionally control for the usual patient risk controls as in the main regression. Standard errors are clustered by facility.

Table 7: **Patient Wellbeing**

	A: OLS Estimates		
	(1) 1(Mobility Decreases)	(2) 1(Develops Ulcers)	(3) 1(Pain Intensity Increases)
1(PE)	0.0324*** (0.003)	0.0078** (0.003)	0.0235*** (0.005)

	B: IV Estimates		
	(1) 1(Mobility Decreases)	(2) 1(Develops Ulcers)	(3) 1(Pain Intensity Increases)
1(PE)	0.0188* (0.010)	-0.001 (0.008)	0.0338** (0.016)
Observations	5,305,056	5,305,056	5,305,056
Y-Mean	0.52	0.08	0.26

Note: This table presents estimates of the relationship between PE ownership and measures of patient wellbeing obtained from clinical assessments. Each cell in Panel A presents the β obtained by estimating Equation (1), and each cell in Panel B presents the IV version of the same results, obtained by estimating Equation (3). The independent variable is an indicator for the patient being admitted to a PE nursing home in Panel A, and is instrumented by differences in distance to the nearest PE and non-PE facility in Panel B. We present results for patient level outcomes - an indicator for decrease in patient mobility, developing/worsening pressure ulcers, and increase in pain intensity. All models include facility and patient HRR x Year fixed effects. We additionally control for the usual patient risk controls as in the main regression. Standard errors are clustered by facility.

Table 8: **Mechanisms and Operational Changes**

	A: Five Star Rating			
	(1) Deficiency Rating	(2) Overall Rating		
1(PE)	-0.075**	-0.079**		
(No Control)	(0.037)	(0.036)		
1(PE)	-0.077**	-0.082**		
(With Control)	(0.037)	(0.036)		
Observations	138,051	138,051		
Y-Mean	2.9	3.2		
	B: Staff Per Patient Day			
	(1) All Staff	(2) Nurse Assistant	(3) Licensed Nurse	(4) Registered Nurse
1(PE)	-0.050***	-0.068***	-0.019***	0.037***
(No Control)	(0.017)	(0.010)	(0.006)	(0.005)
1(PE)	-0.048***	-0.066***	-0.019***	0.037***
(With Control)	(0.016)	(0.010)	(0.006)	(0.005)
Observations	283,767	283,767	283,767	283,767
Y-Mean	3.6	2.3	0.8	0.5
	C: Log Financials			
	(1) Management Fee	(2) Building Lease	(3) Interest Expense	
1(PE)	0.074**	0.564***	1.181***	
(No Control)	(0.032)	(0.061)	(0.096)	
1(PE)	0.074**	0.560***	1.175***	
(With Control)	(0.032)	(0.061)	(0.096)	
Observations	231,556	231,584	231,613	
Y-Mean	0.2	0.4	0.3	

Note: This table presents estimates of the relationship between PE ownership and nursing home outcomes. Each cell presents the coefficient β obtained by estimating equation 10 with a different outcome. The independent variable is an indicator for whether a nursing home is PE-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. Panel A presents results for quality outcomes as measured by Five-star rating awarded by CMS - overall rating and deficiencies identified by independent contractors in audits, respectively. A negative effect on ratings implies a decline in quality. Panel B presents results on per patient nurse availability for all nurses, nurse assistants, licensed nurses, and registered nurses. Panel C presents results on the log of management fees, building lease cost, and interest expenses. The top row presents results with no controls. The bottom row presents the results including controls, which consist of market-level and patient mix controls, as described in Section 6.1. All models include facility and year fixed effects. All variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Appendix: For Online Publication

A Data appendix

This paper uses three primary data sources. We use (1) publicly available nursing home-level data, (2) patient-level administrative claims data, both obtained from CMS, and (3) Pitchbook data on PE deals. This section provides a detailed explanation of these data sources and how we arrived at our analysis samples.

A.1 Nursing Home Data

Our data source on nursing home-level operations and performance is a compilation of information obtained during annual surprise CMS inspector audits and data on nursing home attributes and patient characteristics reported by the facilities themselves.[36] The data span 2000 through 2017. In each year we observe about 15,000 unique nursing homes, for a total of approximately 280,000 observations. Of these, about 13,000 observations represent facilities acquired by PE firms. The aggregate files provide annual data on basic facility attributes, patient volume and case mix, nurse availability, and various components of the Five Star ratings.[37] These ratings started in 2009, so we cannot observe ratings pre-buyout for deals before 2010. Fortunately, half of the PE deals in our sample, accounting for 365 nursing homes, occurred post-2009.

Table 1 Panel A presents summary statistics on the Overall Five Star rating as well as the other key nursing home-level variables used in the analysis. We first present the mean and standard deviation for the whole sample (columns 1-2), then divide observations into two groups—for facilities that are not PE-owned (columns 4-5) and for those that are (columns 6-7). We observe clear differences between PE-owned facilities and those not owned (all statistically significant at the 1% level except where noted). PE targets are slightly larger, have fewer staff hours per resident, and a lower Overall Five Star rating. There have been secular increases for the whole sector in both ratings and staffing over time. For staffing, this reflects more stringent standards from regulators over time. Average staff hours per patient day increased from 3.5 in 2000 to 3.7 in 2017. Similarly, overall average Five Star ratings increased from 2.9 in 2009 to 3.25 in 2017. As the PE deals occurred primarily later in the sample, it is therefore remarkable that they have lower measures of quality on average.

A.2 Patient Data

Our second data source consists of patient-level billing claims and assessment data for Medicare fee-for-service beneficiaries from 2005 to 2016. We observe the universe of billing data for hospital care (inpatient and outpatient) and nursing homes for these beneficiaries, as well as detailed patient assessments recorded in the Minimum Data Set (MDS).[38] We use these files to track beneficiaries' demographics, spending, and health outcomes such as mortality. The MDS helps observe clinical assessments such as mobility.

[36]These files were organized and made available for research by the Long Term Care Focus research center at Brown University. See www.ltcfocus.org for more details.

[37]For more details on how the ratings are produced, see Rating Guide.

[38]Specifically, we use 100% samples of the following: Medicare Beneficiary Summary File (MBSF), Hospital inpatient and outpatient, and Skilled Nursing Facility claims files. These were obtained through a reuse DUA with CMS and accessed through the NBER.

The unit of observation is a nursing home stay for a Medicare beneficiary that begins during our sample period, which we begin in 2005 in order to have at least one look-back year. Our main sample restriction is to identify index nursing home stays for patients, defined as stays that begin at least a year after discharge from a previous nursing home stay. This helps avoid mis-attributing adverse effects to the wrong nursing home. To further avoid attribution error, we consider only the patient's first index stay in our entire sample period. Hence, each patient appears only once in our sample. Using this approach, we settle on a sample of more than 5.3 million patients over 12 years. For each of these patients, we also observe clinical assessments from the MDS, which we successfully match to the claims files. Following the prior literature (Grabowski et al., 2013), we use some other restrictions to arrive at our sample. We restrict to patients over 65 years of age who are enrolled in Medicare parts A and B for at least 12 months before the start of the nursing home stay. This restriction ensures that we observe prior medical care history and pre-existing conditions. We also restrict to stays associated with a hospital visit in the previous month, so that all patients are admitted after a hospital-based procedure and are relatively homogeneous. We drop patients who went to a nursing home in a state other than their state of residence as recorded in the Medicare master beneficiary summary file. This drops a small fraction of patients (less than 5%) and is meant to exclude patients who may be traveling when admitted to a nursing home. Following convention, we drop patients facing a large differential distance value. We exclude zip codes based on the absolute magnitude of the differential distance, treating patients very close to PE facilities the same as those very far away. In practice very few zip codes are more than 20 miles closer to a PE facility. Differential distance values update for some zip codes over time as facilities are acquired or sold by PE firms. We exclude such zip codes only if their differential distance remains more than 20 miles in magnitude throughout. We match the index nursing home stays to the MDS sample on beneficiary ID, facility ID, and admission date. We achieve a match rate of 94% and drop unmatched patients. We drop facilities with fewer than 100 patients over the entire sample period to avoid special facilities and mitigate noise.

Table 1 Panel B presents summary statistics on the final patient-level sample. We use an indicator for death within 90 days following discharge (including during the stay), based on death dates recorded in the Medicare master beneficiary summary file. We use two measures of spending. The first is the total amount that the nursing home bills to Medicare and the patient for the index stay in 2016 dollars. Medicare covers the entire cost until the 21st day of stay, at which point the patient begins paying a coinsurance, which has risen somewhat over time and is now $170.5 per day.[39] In our data, about 90% of total payments are by Medicare. PE-owned facilities charge about 10% more than other facilities. The second measure is the total amount paid for the stay and the 90 days following discharge. This captures any subsequent hospital inpatient or outpatient care, and it provides a more holistic picture of patient care.

Demographic measures associated with risk are quite similar across the types of facilities, including patient age, the share of patients who are black and married, and the Charlson Comorbidity Index, a standard measure of patient mortality risk based on co-morbidities (Charlson et al., 1994).[40] We create a high-risk indicator that is one if the previous-quarter Charlson score is greater than two. According to this definition, about 30% of patients are high-risk. The difference between facility types is not significant.

Finally, we examine three measures of patient well-being which comprise inputs to the

[39]See https://www.resdac.org/cms-data/files/ip-ffs/data-documentationandhttps://www.medicare.gov/Pubs/pdf/10153-Medicare-Skilled-Nursing-Facility-Care.pdf.

[40]The "Charlson score" assigns a point score to each of 17 disease categories recorded during the 3 months before the index stay and sums them to create an overall disease burden score.

quality portion of CMS' Five Star ratings. The first is an indicator for the patient's self-reported mobility score declining during the stay. The second is an indicator for developing a pressure ulcer. The third is an indicator for the patient's self-reported pain intensity score increasing during the stay.

A.3 PE Deal Data

Our primary source of data on PE transactions is a proprietary list of deals in the "Elder and disabled care" sector compiled by Pitchbook Inc., a leading market intelligence firm in this space. The deals span 2004 to 2015. We match the target names to individual nursing facilities using name (facility or corporate owner) and address as recorded in CMS data.[41] Target names in these deals typically refer to holding companies, which often do not reflect the names of individual facilities. The matching process required manual Internet searches to confirm chain affiliations. We supplement the Pitchbook data in two ways. First, we conduct additional Internet searches that yielded a small number of PE deals not reported by Pitchbook. Second, we obtain a list of merger and acquisition deals from 2005 to 2016 from Levin Associates, a market intelligence firm that tracks the healthcare sector. This helps us to identify facilities that did not experience a new PE deal, but were acquired by an existing PE-owned chain.[42]

This process yielded 128 deals, which correspond to a change in ownership to PE for 1,674 facilities. The deals are spread over time (no particular year or part of the business cycle dominates) and across PE firms. Figure C.1 shows the number of deals in each year. In total, our data contain 90 unique PE firms that acquired nursing homes. Most deals are syndicated and involve multiple PE firms. Table C.1 presents the top 5 deals by number of facilities acquired. Deal sizes are skewed, with the top 5 deals accounting more than half the facilities acquired. On average, we observe PE-owned facilities for eight years post-acquisition.[43]

It is difficult to ascertain whether we comprehensively capture PE activity in this sector. While there is no 'official' tally of PE-owned nursing homes to benchmark against, our sample size compares favorably against an estimate of 1,876 nursing homes reportedly acquired by PE firms over a similar duration, 1998–2008 (GAO, 2010). Nonetheless, our analysis likely underestimates the extent of PE activity in nursing homes, as matching between Pitchbook deals and individual facilities is very challenging.

To understand whether deals are concentrated in particular regions, we plot the location of PE-owned facilities across the U.S. in Figure C.3. PE firms appear to be more active in large metropolitan markets, and in certain states such as Florida, Texas, New York, Pennsylvania and Massachusetts. However, there is no obvious concentration, and we do not find systematic variation with local measures of income, age, elder population, or share of patients eligible for Medicare Advantage.

[41]We obtain data on nursing home attributes (name, address, city, owner name and type, number of beds) and quality measures (deficiencies) from Nursing Home Compare. See https://data.medicare.gov/data/nursing-home-compare for more details.

[42]We matched approximately 290 additional facilities using information from the Levin files to the CMS data. Of these, about 40 were PE-owned.

[43]A likely source of measurement error is not capturing PE disinvestment from facility ownership. For the top 10 deals we verified PE exit via manual internet searches and incorporated it in the analysis. The main results are robust to dropping observations of facilities that have been owned by PEs for 10 years or more. As expected, the coefficients modestly increase in magnitude when we do so.

A.4 Targeting

This paper does not address why nursing homes may or may not be profitable acquisition targets, and does not assess returns from investing. However, exploring what types of facilities are targeted can help to interpret the effects of buyouts on patient welfare and is also useful for identifying the most relevant control variables for our empirical analysis. We describe which characteristics are robustly associated with buyouts in Table A.1, which presents estimates of Equation (12):

$$PE_{j,t} = \alpha_s + \alpha_t + X'_{j,t}\beta + \epsilon_{j,t} \tag{12}$$

Here, $PE_{j,t}$ is set to 100 if the facility j is acquired in a PE deal in year t (we drop all years post-deal, and multiply by 100 for ease of reading). $PE_{j,t}$ is zero for never-PE and PE-owned facilities before the deal. We include state and year fixed effects.

We report models including variables known to be central to nursing home quality of care and economics or that are potentially important and robustly predict buyouts. In column 1, we find that facilities in more urban counties are more likely to be targeted.[44] Urban nursing homes tend to be closer to hospitals and likely enjoy thicker labor markets. Facilities in a state with a higher ratio of elderly people are also more likely to be targeted. County-level income, race, and home ownership do not predict buyouts. Results for these covariates are not presented.

In column 2, we turn to facility characteristics. Chains are more likely to be acquired than independent facilities, likely reflecting substantial fixed costs in deal-making. Hospital-owned facilities are less likely to be targeted. PE firms also tend to target larger and higher-occupancy facilities. We consider patient-level characteristics in column 3: the share of the nursing home's patients covered by Medicaid, the share on private insurance, and the share who are Black. The first two are strongly negatively associated with buyouts, meaning that a higher share of Medicare patients (the omitted group) is positively associated with being targeted. In column 4, we assess two facility-level quality measures we employ in the analysis: Five Star overall rating and staff hours per patient day. Both are negatively associated with buyouts, but once we control for rating, staffing is not significant. These results indicate that PE firms target relatively low-performing nursing homes.

Finally, in column 5 we include simultaneously all of the variables from the previous models that had predictive power. Some, such as admits per bed and hospital ownership, become small and insignificant after controlling for the other variables. Notably, the state elder ratio, chain indicator, and Five Star rating retain their magnitudes and precision.

[44] We define urban as being in the top 2 out of 9 county groups classified as urban based on a Department of Housing and Urban Development 2003 rural-urban classification.

Table A.1: **Targeting**

	Mean	(1)	(2)	(3)	(4)	(5)
Urban Indicator	0.56	0.193***				0.105**
		(0.037)				(0.041)
State Elder Ratio	0.24	4.340***				18.819***
		(1.328)				(3.906)
1(Chain)	0.53		0.835***			0.367***
			(0.033)			(0.029)
Hospital-Owned	0.07		-0.221***			-0.003
			(0.053)			(0.067)
Log(Beds)	4.5		0.287***			0.086***
			(0.030)			(0.032)
Admits Per Bed	2.08		0.051***			0.009
			(0.007)			(0.015)
Ratio Medicaid	0.60			-0.879***		-0.434*
				(0.117)		(0.229)
Ratio Private	0.25			-1.441***		-0.422*
				(0.144)		(0.236)
Ratio Black	0.10			0.002		
				(0.099)		
Overall Rating	3.15				-0.075***	-0.066***
					(0.015)	(0.015)
Staff Hr per Patient Day	3.55				-0.022	
					(0.018)	
Observations		235,670	218,592	218,592	103,831	103,831
Y-Mean (pp)		0.6	0.6	0.6	0.6	0.6

Note: This table shows estimates of the relationship between pre-existing nursing home characteristics and whether a nursing home is a target of a PE buyout. Column 1 presents market-level attributes: an indicator for urban and the share of state population which is elderly. Column 2 presents facility-level attributes: indicator for being member of a chain, indicator for the nursing home being hospital-based, the log number of beds, and admits per bed. Column 3 presents patient mix controls: share of patients covered by Medicaid, share of patients who pay privately, and the share of patients who are black. Column 4 presents quality metrics such as Five-star ratings awarded by CMS and staff hours per patient day. We re-run the regression on all variables which appear significant in Columns 1 to 4 in Column 5. The dependent variable is 100 if the nursing home was acquired by PE in that year and 0 otherwise. We remove all observations of private equity-owned facilities in years following the take-over by PE. We control for state and year FEs. Standard errors are clustered by facility.

B Instrument Validation & Robustness Tests

Instrument Validation

This section discusses tests of the identification assumptions behind the instrument not described in the main text. Two tests are related to the conditional randomization assumption. First, PE firms may strategically target more lucrative zip codes within an HRR. If patients in these zip codes have higher mortality, the exclusion restriction might be violated. A first test of this possibility is to impose a more granular market definition, the Hospital Service Areas (HSA). There are nearly 3,400 HSAs, while there are only about 300 HRRs. If neighborhood targeting explains our result, we expect the instrument to work less well at this level. Table 3 column 4 presents results using this market definition and finds similar patterns (below, we also show similar results in the second stage analysis). Two other tests of this hypothesis are presented below after the main results.

Second, PE funds may strategically target nursing homes located in places with certain desired demographic and risk profiles. We account for stable differences in the patient catchment of facilities by including facility fixed effects. However, it is possible that PE firms strategically target neighborhoods with desirable trends, for example with increasing household income. We show that the results are robust to including time-varying zip code-level socioeconomic controls. We document that these controls do not affect the first stage in Column 3 of Table 3. We flexibly allow HRRs to evolve on different trends to mitigate the possibility of differences in market structure confounding our results.

The monotonicity assumption implies that the first stage should be negative when estimated on sub-samples of patients with different characteristics. Table C.2 shows that when we estimate the relationship between below-median differential distance and PE ownership (a simplified first stage), we recover coefficients that are very similar to the full-sample result and all are significant at the .01 level for a variety of sample splits by age, gender, race, and zipcode income level.

In another falsification check, following the tests proposed in Angrist et al. (2010) and Grennan et al. (2018), we limit the sample to patient groups where we would expect differential distance to have weak influence over facility choice. For example, patients that are relatively very far or very close to PE facilities are likely insensitive to small changes in distance. Similarly, patients who face similar distances to both types of facilities (within one mile) are unlikely to choose based on this differential. Table C.4 presents results from first stage and reduced form models (with mortality as the outcome) for such patient groups and compares them to the main analysis sample (in column 1). The first stage is orders of magnitude weaker for these groups, and the test statistic of joint significance for the differential distance and its squared term is typically well below the conventional threshold for weak instruments. These patterns reassure us that the instrument behaves according to expectations. More importantly, we find a similar pattern for the reduced form model coefficients. Hence, the instrument does not provide explanatory power for patient mortality in the cases where it does not predict facility choice. This evidence counters the possibility of a spurious relationship between differential distance and mortality.

Table C.2 also helps characterize compliers relative to the average patient at a PE facility. The ratio of the first stage coefficient for a subsample with a specific attribute to that obtained for the full sample provides the likelihood of compliers having that particular attribute relative to the average PE patient.[45] Compliers appear to have a very similar age distribution (not

[45]This follows from Bayes rule and the use of a discrete instrument in this model of the first stage. The

presented) and the probability of being male, married, or white. Intuitively, distance-based compliers are slightly more likely to be from a low-income zipcode.

Robustness Tests

We present results from specification and falsification checks to address potential concerns with our empirical analysis. First, we implement a placebo analysis to probe whether spurious factors or pre-existing trends rather than the ownership change might explain the results. We use Medicare patient-level data from 2002–07, a period with little PE ownership of nursing homes and little overlap with our main sample (2005-16). We assign placebo PE acquisition in 2004 to facilities that were eventually acquired before 2008 and 2005 to facilities acquired in and post 2008 by PE firms. Further, we discard data for any facility starting with the year it actually got acquired. We recompute differential distances under these 'placebo' assignments and estimate our main IV models. Table 2 Panel D presents these placebo estimates and reassuringly finds small and insignificant effects, implying a lack of differential trends prior to acquisition.

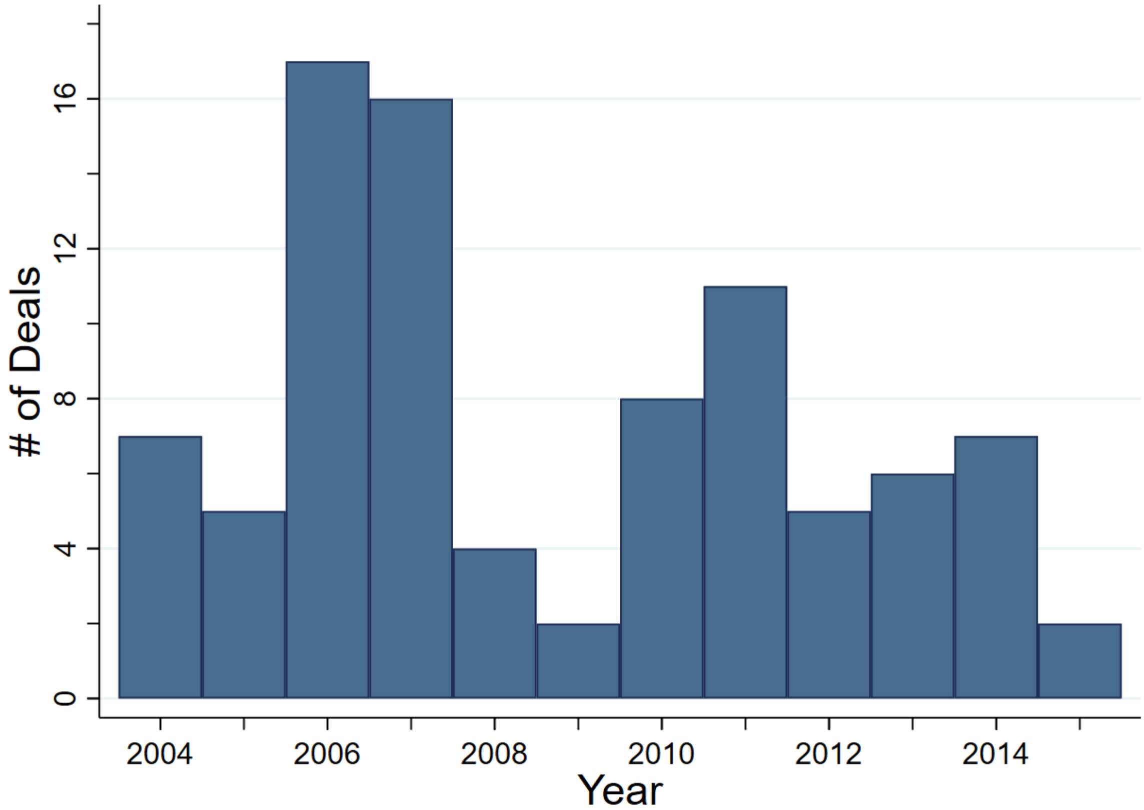
Table 5 row 2 reports specification checks that vary the controls and market definition. If the instrument does not randomly assign patient risk, we expect patient controls to substantially affect the results. In row 2.A, we omit all patient controls. In row 2.B., we include zip-year socioeconomic controls. In row 2.C, we use more granular HSAs instead of HRRs to define patient markets. In row 3, we limit the patient sample using a stricter differential distance threshold of 10 miles instead of 20 miles. This ensures the patient sample is even more homogeneous. In row 4, we change the functional form of our specification and use an indicator of differential distance greater than median rather than a continuously varying value. Across all these changes, the coefficients remain within two standard errors of the main estimates in row 1. In row 5, we cluster standard errors by deal rather than by facility. Accordingly, the confidence intervals widen, but the coefficients remain statistically significant.

In addition to varying the sample and right-hand side variables, we also establish that the effect on mortality is robust to alternative durations. The results using time horizons from 15 to 365 days following discharge from the nursing home stay are shown in Table C.5. The effect on mortality is significant and similar as a percent of the mean to the main result in all models. For example, the effect is 13% when mortality is measured at 30 days following discharge, and 11% when measured at 365 days.

coefficient from a subsample with attribute X is $P(M|X) = P(X|M)P(M)/P(X)$ where M denotes a marginal PE patient. Dividing by the first stage coefficient for the full sample, $P(M)$, gives us $P(X|M)/P(X)$, the relative likelihood.

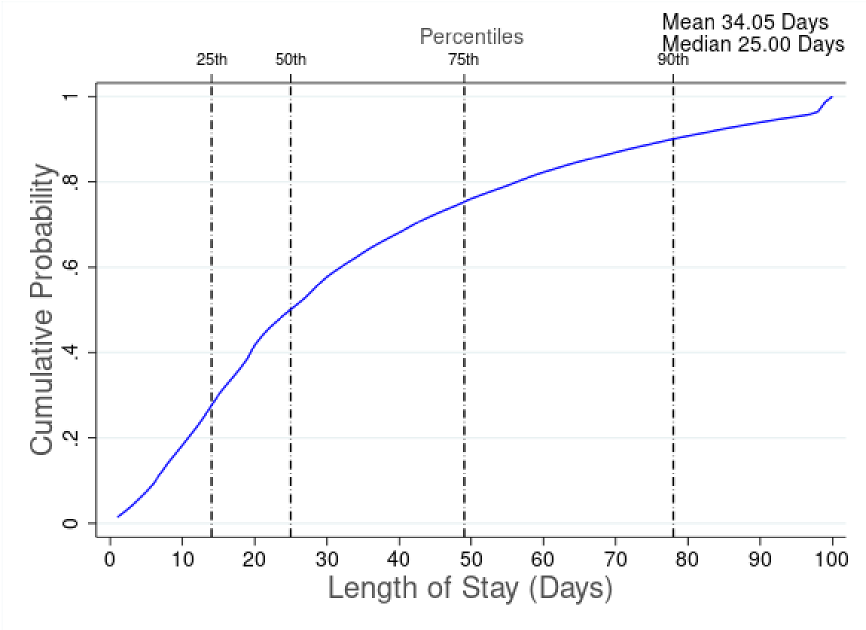
C Supplementary Figures and Tables

Figure C.1: **PE Deals for Nursing Homes by Year**

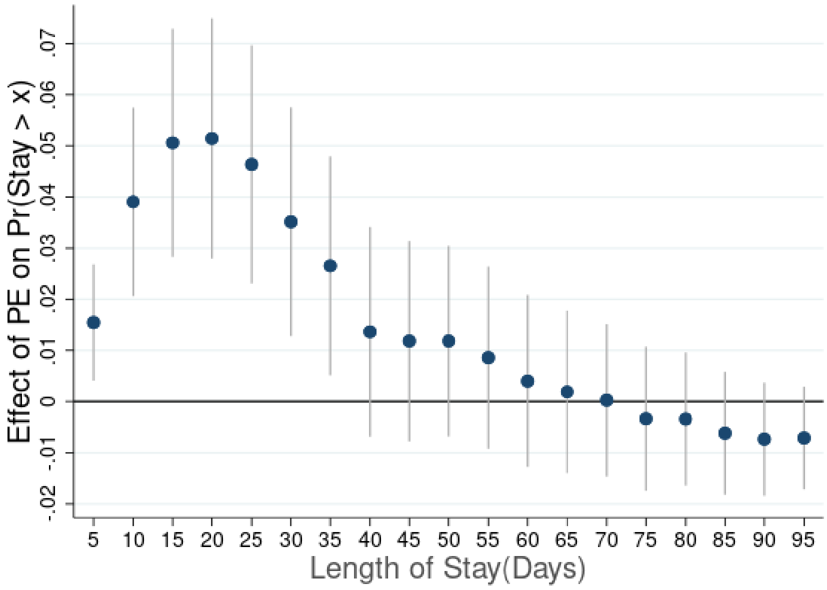


Note: This figure presents the number of unique deals for active nursing homes by PE firms for each year over the period 2004–2015.

Figure C.2: **Patient Length of Stay**



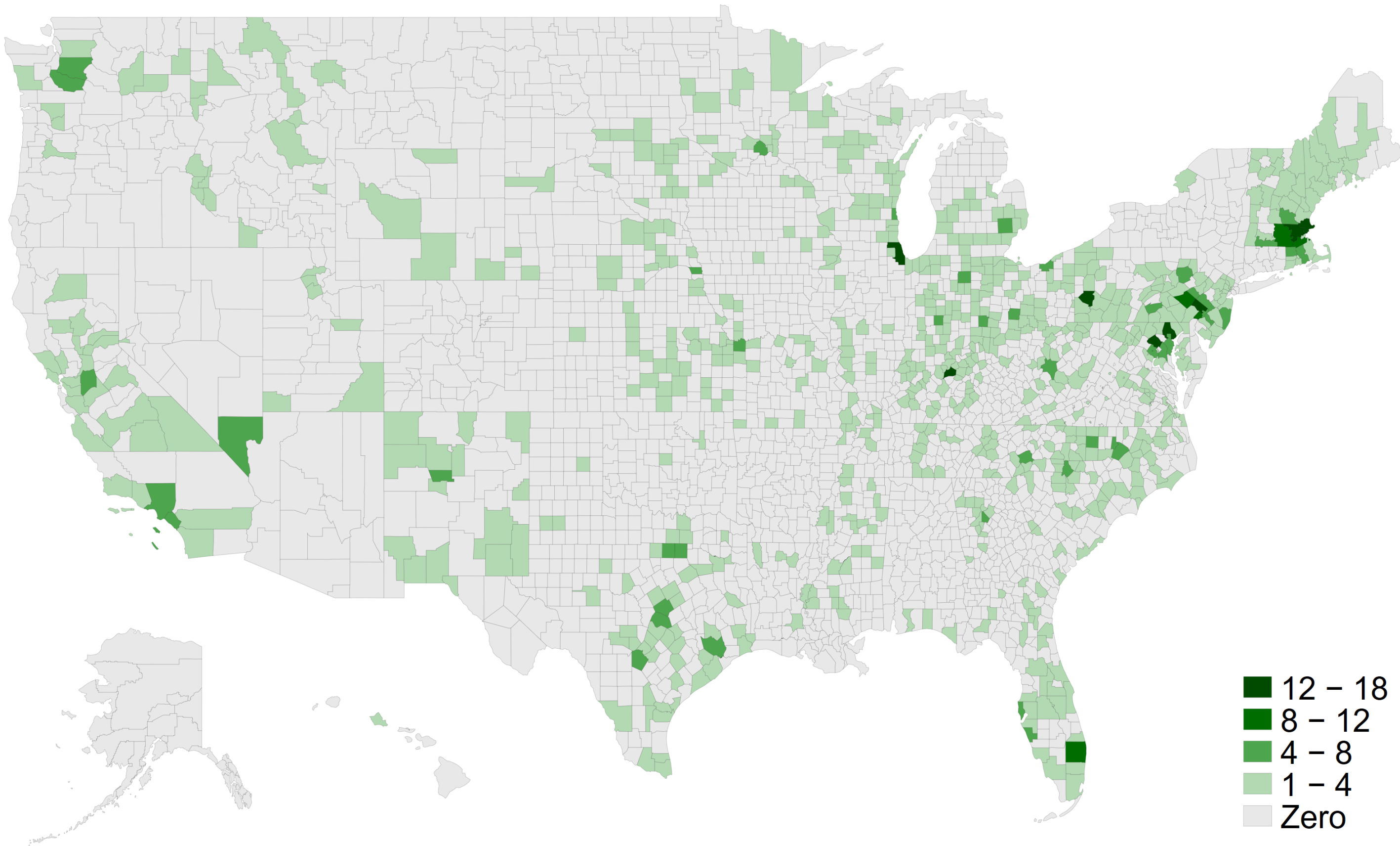
A: Length of Stay Distribution



B: Effect on Length of Stay

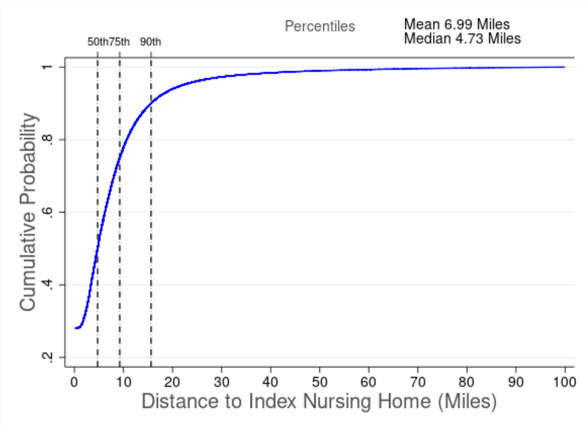
Note: This figure presents plots relating to patient length of stay. Panel A presents a histogram of the cumulative probability for patient length of stay (in days). Panel B presents estimates for effect of private equity on shift in distribution of length of stay. For Panel B, the x-axis represents the length of stay (in days) and the y-axis represents the coefficient β for the probability that length of stay is greater than the number of days as specified on the x-axis. Each blue point in the figure is obtained by separately estimating β using Equation (2) with the dependent variable being an indicator which equals one if length of stay for patient is greater than corresponding value on x-axis. As an example, the dependent variable for the first point (x = 5 days) is an indicator which equals one if patient length of stay is greater than 5 days. The equation is estimated via 2SLS where independent variable is an indicator for the patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest PE and non-PE facility. Regressions include facility and patient HRR x Year fixed effects, and patient risk controls. Patient risk controls include age, race, gender, marital status, indicators for 17 pre-existing conditions used to compute the Charlson Index, and an indicator if patients are dual eligible. Standard errors are clustered by facility.

Figure C.3: **Location of Private Equity Targets**

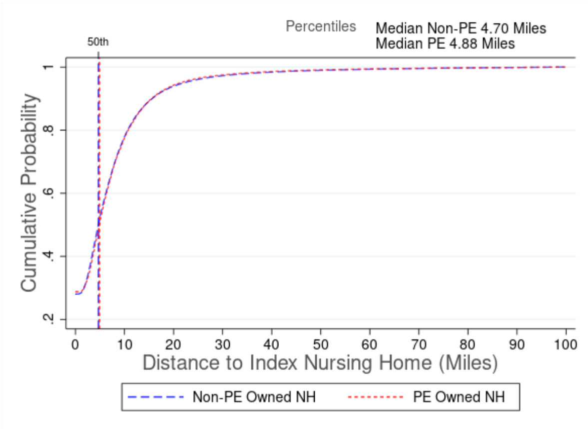


Note: This figure presents the number of facilities bought by PE firms in each county over the period 2004–2015. We identified 1,674 such facilities.

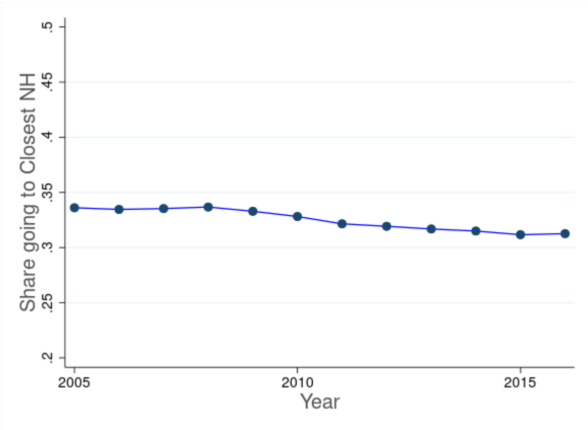
Figure C.4: **Patient Distance to Nursing Home**



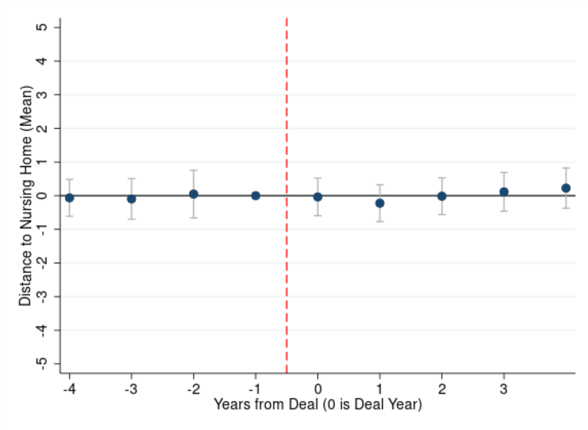
A: CDF: All Patients



B: CDF: PE vs. Non-PE Patients



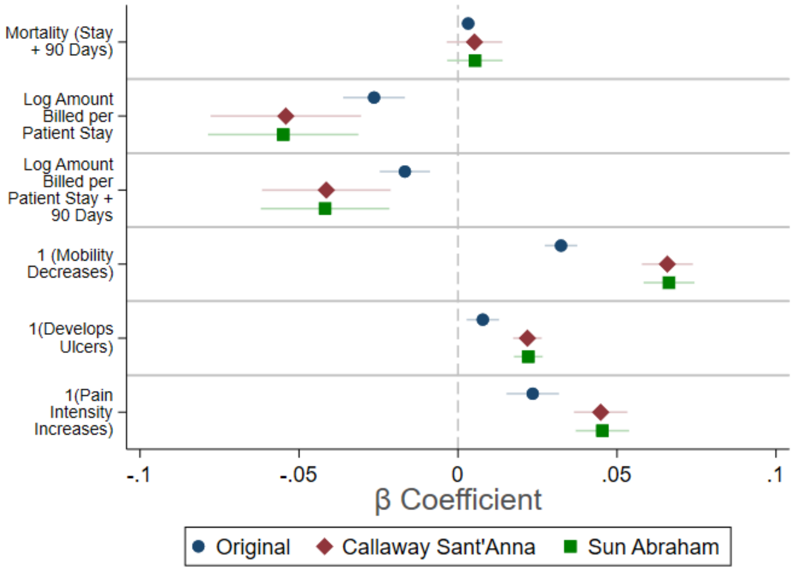
C: Trendline: Share going to Closest Nursing Home



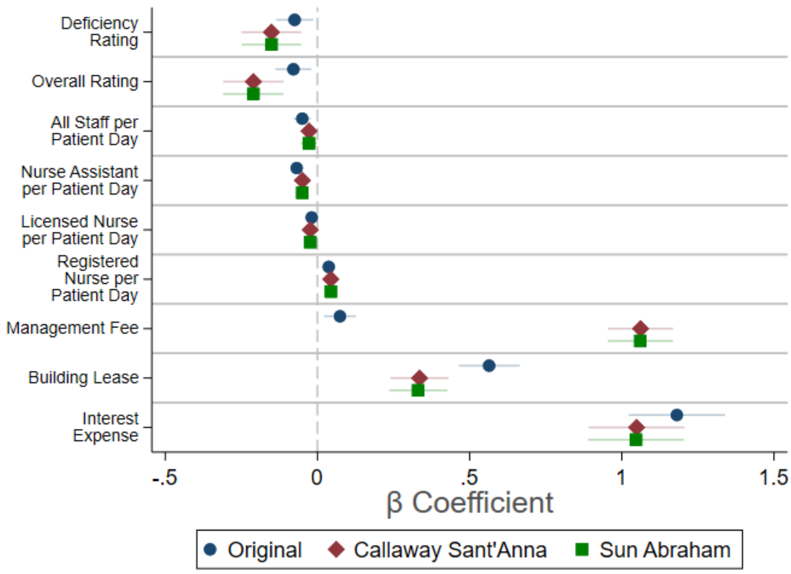
D: Event Study: PE Acquisition

Note: This figure provides descriptives on patient zip code distance to index nursing home zip code. Panels A and B present CDFs of the distance from patient zip code to index nursing home zip code. Panel A presents the CDF pooling PE and non-PE patients together. It also identifies the median, 75th and 90th percentile values. Panel B presents the CDFs separately for PE and non-PE patients, and their respective median values. Panel C presents the annual trendline for the share of patients going to their closest nursing home. Panel D presents the event study of the mean patient distance around a PE acquisition. Each point in the figure represents the coefficient β_s obtained by estimating Equation (11) as discussed in Section 6. Year = -1 is the omitted point. The model includes facility and HRR x year fixed effects, patient mix, and market controls. Standard errors are clustered by facility.

Figure C.5: **OLS Results with Alternative Estimators**



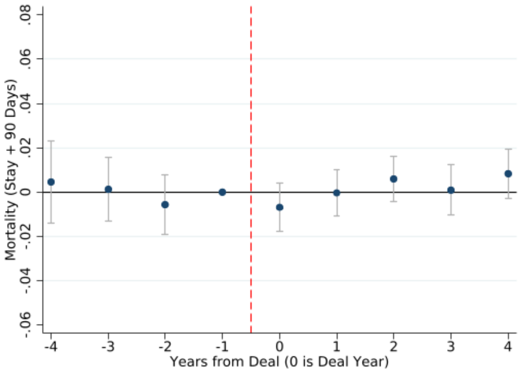
A: Patient-Level Outcomes



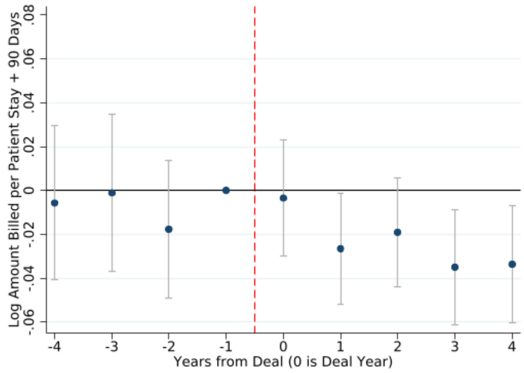
B: Facility-Level Outcomes

Note: This figure presents reports coefficients and 90% confidence intervals for the Callaway and Sant'Anna (2021) and Sun and Abraham (2021) alternative estimators for all outcomes. Panel A shows the three patient-level outcomes, while Panel B shows the nine facility-level outcomes. These address potential bias in the size or direction of coefficients from staggered differences-in-differences models.

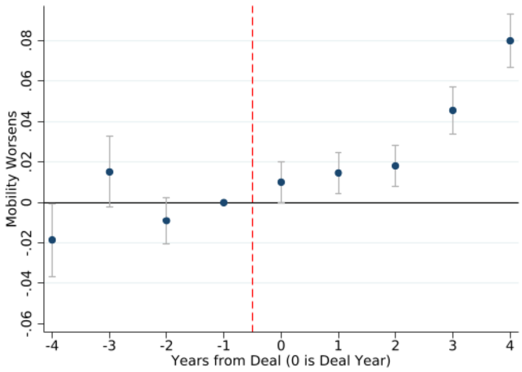
Figure C.6: **Patient Outcome Measures**



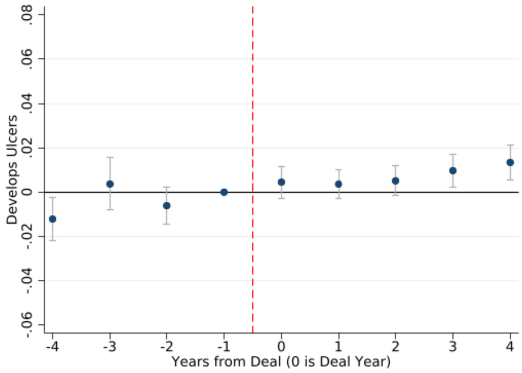
A: Mortality (Stay + 90 Days)



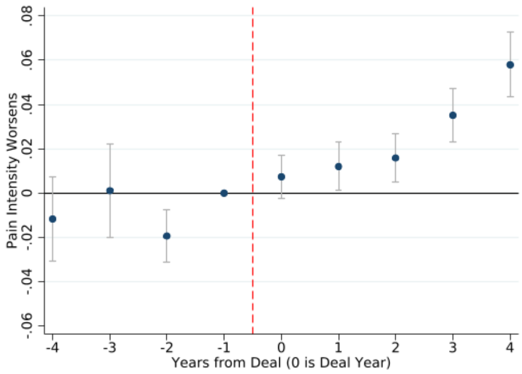
B: Log Amount Billed (Patient Stay + 90 Days)



C: 1(Mobility Decreases)



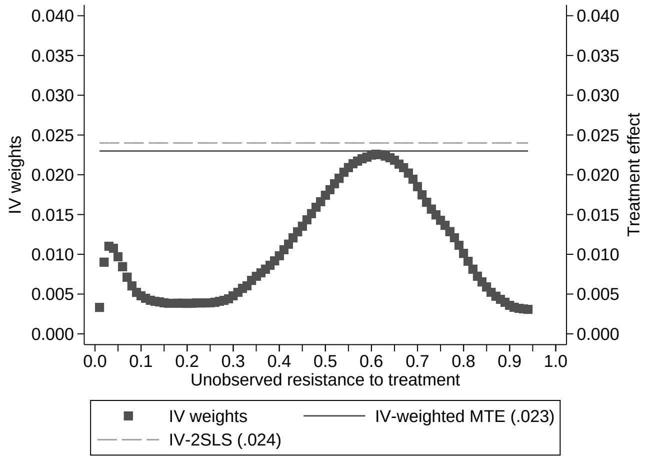
D: 1(Develops Ulcers)



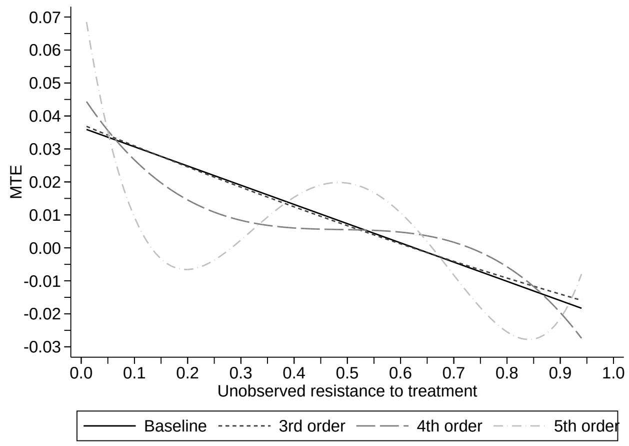
E: 1(Pain Intensity Increases)

Note: This figure presents event studies on patient outcome measures around the time a nursing home experiences a PE buyout. These models were estimated on collapsed facility-year level data using an event study version of Equation (1). Year = -1 is the omitted point. Panels A and B present results on the share of patients dying within 90 days of discharge from the index stay, and total amount billed over the 90-day episode including the index stay (2016$). Panels C to E present results for MDS assessment based outcomes - the facility level mean for indicators for decrease in patient mobility, developing/worsening pressure ulcers, and increase in pain intensity respectively. Spending is winsorized at the 1% and 99% level. Standard errors are clustered by facility.

Figure C.7: **MTE Specification Checks**



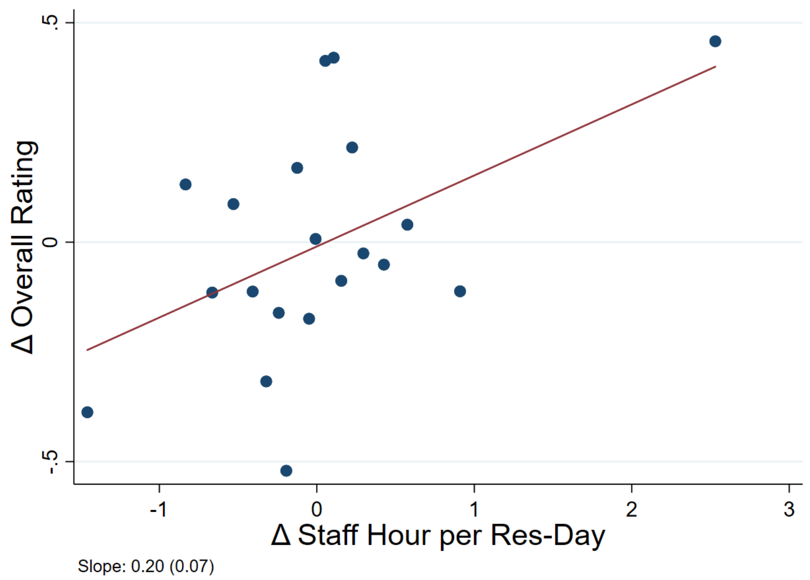
A: IV estimate



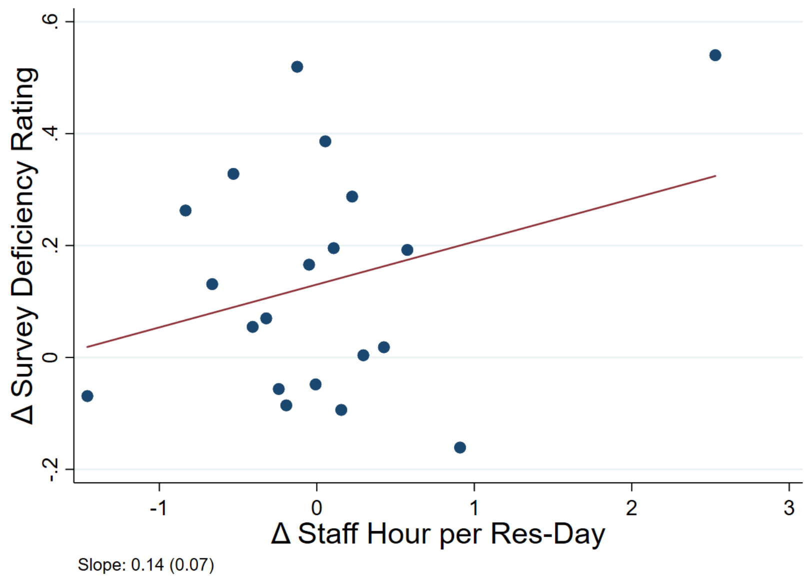
B: Order of polynomial

Note: This figure presents results from specification checks pertaining to the Marginal Treatment Effects (MTE) analysis. Panel A tests robustness of the slope of the MTE curve to using different orders of polynomials. Panel B presents the weights to compute the weighted average equivalent of the 2SLS estimate (left axis) and the weighted average value (solid line, right axis). The figure also indicates the 2SLS estimate (dashed line) presented in the main results. Section 5.2 presents details of the MTE estimation.

Figure C.8: **Staff Availability and Five Star Ratings**



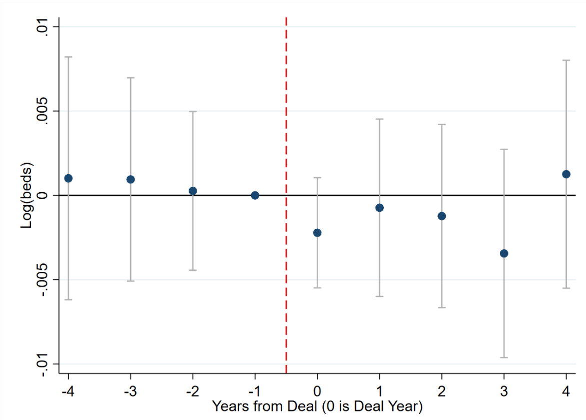
A: Overall Rating



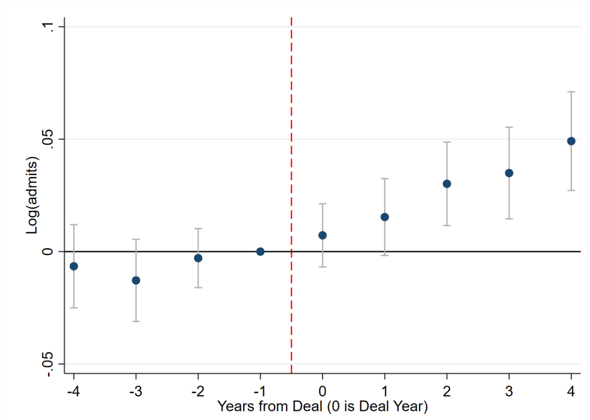
B: Deficiency Rating

Note: This figure presents scatter plots of changes in total staff hours available per patient day in the three years post-PE buyout versus three years pre-buyout on the X-axis, against changes in CMS Five-star rating over the same period on the Y-axis. Panel A presents overall rating, and Panel B presents survey based deficiency ratings. The data was collapsed into 20 equal sized bins and we plot the means in each bin. The figures also present fitted lines for these plots obtained using linear regressions on the underlying data. Each plot also presents the slope coefficient with standard error.

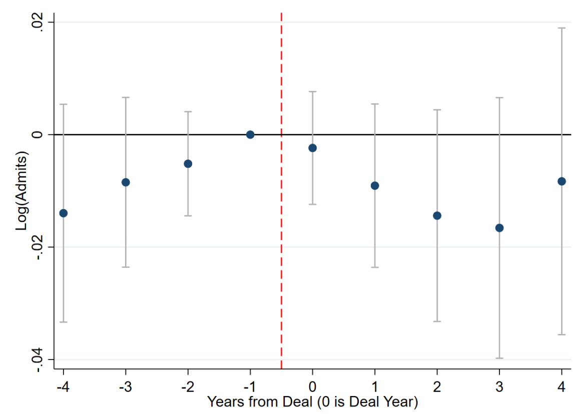
Figure C.9: **Patient Volume**



A: Log Beds - Facility



B: Log Admissions - Facility



C: Log Admissions - Market (HRR)

Note: This figure presents event studies on facility characteristics around the time a nursing home experiences a PE buyout. Each point in the figures represents the coefficient β_s obtained by estimating Equation (11) as discussed in Section 6. Year = -1 is the omitted point. Panels A and B present results on the log of beds and admissions at the facility level, and Panel C on log admissions at the market level (HRR). All models – except when studying market-level volume – include facility and year fixed effects, patient mix, and market controls, as described in Section 6.1. All dependent variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Table C.1: **Top 5 Private Equity Deals**

Sr. No.	**Target Name**	**Private Equity Firm(s)**	**Deal Year**	**Number of Facilities**
1	Genesis Healthcare	Formation Capital, JER Partners	2007–15	327
2	Golden Living	Fillmore Capital Partners	2006	321
3	Kindred Healthcare	Signature Healthcare, Hillview Capital	2014	150
4	HCR Manorcare	Stockwell Capital, The Carlyle Group	2007–18	145
5	Mariner Healthcare	Fillmore Capital Partners	2004	95

Note: This table presents some details on the top 5 PE deals in our sample, ordered by the number of unique nursing home facilities involved in the deal. This represents the number of facilities we were able to identify and match in our administrative data, the actual number of facilities in the deal may have been different. We set the PE indicator to turn on in the year following the deal year. If a closing year is mentioned, it implies the PE investors exited or went public in that year. Accordingly, we turn off the PE indicator in the closing year.

Table C.2: **Complier Characteristics**

	Observations	Coefficient	(Std. Errors)	Ratio
Full Sample	5,305,056	-0.0450***	(0.002)	
A. Risk				
Low Risk	3,874,419	-0.0438***	(0.002)	0.97
High Risk	1,430,247	-0.0481***	(0.003)	1.07
B. Gender				
Male	1,911,713	-0.0469***	(0.003)	1.04
Female	3,392,983	-0.0439***	(0.002)	0.98
C. Marital Status				
Unmarried	3,456,941	-0.0448***	(0.002)	1.00
Married	1,847,768	-0.0448***	(0.003)	1.00
D. Beneficiary Zip Income				
Income < Median	2,651,778	-0.0525***	(0.003)	1.17
Income > Median	2,652,600	-0.0401***	(0.003)	0.89
E. Race				
White	4,666,385	-0.0462***	(0.003)	1.03
Other	637,718	-0.0343***	(0.003)	0.76

Note: This table presents first stage equivalent estimates of the 2SLS for various patient subsamples. We present the coefficient β, obtained by estimating the equation $PE_i = \alpha_j + \alpha_{m,t} + \beta\, 1(DD_i > Median) + \epsilon_i$. $1(DD_i > Median)$ is an indicator for patient i's differential distance to the nearest PE-owned facility being greater than the median value. The model includes facility j and patient HRR x year fixed effects, but no other controls. We divide the sample by risk, gender, marital status, income in patient zip code, and race. We also present the ratio of the coefficient obtained for each subsample to that for the full sample. Standard errors are clustered by facilities.

Table C.3: **Mortality Costs**

	(1) Male	(2) Female
A: IV estimates		
1(PE)	0.0252**	0.0229***
	(0.013)	(0.009)
Observations	1,911,713	3,392,983
Y-Mean	0.22	0.15
F-Stat	227	217
B: Placebo		
1(PE)	0.0054	-0.0012
	(0.006)	(0.005)
Observations	1,703,760	3,168,697
Y-Mean	0.24	0.16
F-Stat	522	494
C: Calculations		
Number of Patients in PE Facilities	435,035	741,838
Additional Deaths	10,963	16,988
Total Lives Lost	27,951	
Mean Life Expectancy	6.8	8.2
Additional Loss in Person Years	74,224	139,358
Total Person Years Lost	213,582	
Value of Life Year (2016 $)	130,000	
Total Cost (2016 $)	27.77 Billion	

Note: This table presents estimates of additional deaths, life-years lost, and the associated cost using standard estimates of statistical value of a life-year due to PE ownership of nursing homes. Panel A presents the coefficient β obtained by estimating Equation (3) by 2SLS. The independent variable is the indicator for a patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest non-PE and PE nursing home. The outcome variable is an indicator for patient death within 90 days of discharge from the index stay. Panel B presents a placebo analysis for this patient subsample using the same approach as for the whole sample, as presented in Table 2. All models include facility and patient HRR x year fixed effects and the usual patient risk controls as in the main specification. Standard errors are clustered by facility. Panel C presents calculations to estimate lives, life-years lost and total cost based on Panel A coefficients. We calculate average life expectancy at discharge (by gender) using the observed distribution of lifespans for Medicare patients. For patients still alive at the end of our sample, we assign a year of death based on patient gender and age using Social Security actuary tables. We adjust downward the resulting life expectancy to account for the fact the decedents tend to be older than the average nursing home patient (about two years).

Table C.4: **Effects By Differential Distance**

	Differential Distance (in miles)					
	(1) Base sample	(2) -1 < DD < 1	(3) DD > 20	(4) DD > 30	(5) DD > 40	(6) DD > 50
First Stage						
F stat	227.74	0.25	17.66	5.86	0.48	0.47
p-value	0.00	0.78	0.00	0.00	0.62	0.63
Reduced Form						
F stat	5.50	1.04	0.81	1.94	2.88	0.71
p-value	0.00	0.36	0.45	0.14	0.06	0.49
Observations	5,321,919	261,062	1,127,435	583,765	308,988	148,275

Note: This table presents the F-statistic and *p*-value from the joint test of significance on the differential distance coefficients in the first stage and reduced form (with 90-day mortality as the outcome) models for different patient sub-groups. Column 1 presents estimates from our main sample, where the differential distance (DD) is less than 20 miles in magnitude ($-20 \leq DD \leq 20$). Column 2 onwards we replicate the first stage and reduced form models on different sub-groups based on the differential distance values. For example, in Column 2 we only retain patients residing in zip codes such that their distances to PE and non-PE facilities are very similar (differ by < 1 mile). Column 3 only retains patients located in zip codes that are at least 20 miles further away from a PE facility relative to a non-PE facility. Columns 4, 5, and 6 are similarly defined. All models include patient controls, facility, and HRR × year fixed effects. Standard errors are clustered by facility.

Table C.5: **Mortality Effects by Duration**

	(1) (Stay + 15 Days)	(2) (Stay + 30 Days)	(3) (Stay + 60 Days)	(4) (Stay + 90 Days)	(5) (Stay + 365 Days)
1(PE)	0.0124**	0.0151**	0.0238***	0.0241***	0.0274***
	(0.006)	(0.007)	(0.007)	(0.008)	(0.009)
Observations	5,305,056	5,305,056	5,305,056	5,305,056	5,305,056
Y-Mean	0.09	0.12	0.15	0.18	0.24
F-Stat	224	224	224	224	224
Coefficient/ Y-Mean	14%	13%	15%	13%	11%

Note: This table presents estimates of the relationship between PE ownership and patient mortality. Each cell presents the coefficient β obtained by estimating Equation (3) by 2SLS. The independent variable is an indicator for the patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest PE and non-PE facility. We present effects for mortality at different durations - patient death within 15, 30, 60, 90, and 365 days of discharge from the index stay. All regressions include facility and patient HRR x year fixed effects, and patient risk controls. Patient risk controls include age, race, gender, marital status, indicators for 17 pre-existing conditions used to compute the Charlson Index, and an indicator for dual eligibility. Standard errors are clustered by facility.

Table C.6: **Patient Sourcing & Discharge**

	A: Upstream (Discharge from Hospital)		
	HRR	HSA	County
	(1) Discharge to Nursing Home	(2) Discharge to Nursing Home	(3) Discharge to Nursing Home
1(PE)	0.000	0.002	0.001
	(0.002)	(0.002)	(0.002)
Observations	29,900,000	29,900,000	29,900,000
Y-Mean	0.14	0.14	0.14
	B: Downstream (Discharge from Nursing Home)		
	(1) Discharge to Home	(2) Discharge to Facility	(3) Discharge to Other
1(PE)	0.015	-0.018	0.003
	(0.012)	(0.011)	(0.010)
Observations	5,305,056	5,305,056	5,305,056
Y-Mean	0.58	0.25	0.16
F-Stat	224	224	224

Note: This table presents estimates for effects on PE on patient admissions from hospitals to nursing homes and on discharge from nursing homes. Panel A presents results for Upstream - discharge from hospitals to nursing homes. We present the coefficient β, obtained by estimating the equation $Y_{i,j,t} = \alpha_j + \alpha_t + \beta PE_{j,t} + X_i + \epsilon_i$. $PE_{j,t}$ is an indicator whether hospital j's market has PE owned nursing home (=1 if PE-owned, 0 otherwise) in year t. Column 1 defines markets based on HRR, Column 2 on HSA, and Column 3 on County. The model includes hospital j and year fixed effects, and controls for patient risk: age, gender, and indicators for 17 pre-existing conditions used to compute the Charlson score. Standard errors are clustered by hospitals. Panel B presents results for Downstream Channel - discharge from nursing homes to different facilities. Each cell presents the coefficient β obtained by estimating Equation (3) by 2SLS. The independent variable is an indicator for the patient being admitted to a PE nursing home, instrumented by differences in distance to the nearest PE and non-PE facility. We present probability of discharge to patient residence, facility (including hospitals, long stay nursing homes and hospice), and all other discharges. All regressions include facility and patient HRR x year fixed effects, and patient risk controls. Patient risk controls include age, race, gender, marital status, indicators for 17 pre-existing conditions used to compute the Charlson Index, and an indicator for dual eligibility. Standard errors are clustered by facility.

Table C.7: **Effects on Quality by Share Revenue from Medicare**

	A: Five Star Rating			
	Deficiency Rating		Overall Rating	
	Medicare < Median	Medicare > Median	Medicare < Median	Medicare > Median
	(1)	(2)	(3)	(4)
1(PE)	0.029	-0.118***	-0.029	-0.099**
(No Control)	(0.071)	(0.043)	(0.071)	(0.042)
1(PE)	0.028	-0.122***	-0.031	-0.104**
(With Control)	(0.071)	(0.043)	(0.071)	(0.042)
Observations	69,668	68,383	69,668	68,383
Y-Mean	2.9	2.8	3.2	3.2

Note: This table presents estimates of the relationship between PE ownership and nursing home quality as measured by the Five Start ratings. We repeat the models in Table 8 Panel A, but divide the sample by whether the nursing home's revenue from Medicare is above or below the median. Each cell presents the coefficient β obtained by estimating Equation 10. The independent variable is an indicator for whether a nursing home is PE-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. All models include facility and year fixed effects. All variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Table C.8: **Robustness: Facility-Level Outcomes**

	A: Five Star Rating			
	(1) Deficiency Rating	(2) Overall Rating		
1. Chain Controls				
1(PE)	-0.074**	-0.079**		
	(0.036)	(0.028)		
2. W/O Top 2 Deals				
1(PE)	-0.145***	-0.204***		
	(0.050)	(0.042)		
3. Only For Profit				
1(PE)	-0.077**	-0.082**		
	(0.036)	(0.028)		
Observations	138,051	138,051		
Y-Mean	2.9	3.2		
	B: Staff Per Patient Day			
	(1) All Staff	(2) Nurse Assistant	(3) Licensed Nurse	(4) Registered Nurse
1. Chain Controls				
1(PE)	-0.050***	-0.068***	-0.019***	0.037***
	(0.016)	(0.010)	(0.006)	(0.005)
2. W/O Top 2 Deals				
1(PE)	-0.100***	-0.101***	-0.021**	0.030***
	(0.026)	(0.015)	(0.009)	(0.008)
3. Only For Profit				
1(PE)	-0.045***	-0.062***	-0.024***	0.039***
	(0.017)	(0.010)	(0.006)	(0.005)
Observations	283,767	283,767	283,767	283,767
Y-Mean	3.6	2.3	0.8	0.5
	C: Log Financials			
	(1) Management Fee	(2) Building Lease	(3) Interest Expense	
1. Chain Controls				
1(PE)	0.074**	0.564***	1.181***	
	(0.032)	(0.061)	(0.096)	
2. W/O Top 2 Deals				
1(PE)	0.042	0.809***	2.048***	
	(0.050)	(0.102)	(0.160)	
3. Only For Profit				
1(PE)	0.056*	0.570***	1.179***	
	(0.032)	(0.061)	(0.096)	
Observations	231,556	231,584	231,613	
Y-Mean	0.2	0.4	0.3	

Note: This table presents robustness tests on the estimates of the relationship between PE buyouts and Five Star ratings, nurse availability, and financials. The corresponding main results are presented in Table 8. Each cell presents the coefficient β obtained by estimating Equation (10) with a different outcome. The independent variable is an indicator for whether a nursing home is PE-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. We control for a chain indicator in the first row, remove the top 2 deals by size in the second row, and estimate the results on a sample limited to for-profit facilities in the third row. We do not present results limiting to the Top 5 deals as Five Star ratings are only available post-2009, and 4 Top 5 deals occurred before 2009. All models include facility and year fixed effects. All variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Table C.9: **Goodman-Bacon Decomposition: Facility-Level Outcomes**

	A: Five Star Rating	
	(1) Deficiency Rating	(2) Overall Rating
Overall		
1(PE)	-0.0336	-0.1681***
	(0.059)	(0.061)
Never PE vs. Timing		
1(PE)	-0.0330	-0.1598
Weight	0.91	0.91
Always PE vs. Timing		
1(PE)	-0.0342	-0.2066
Weight	0.08	0.08
Observations	83,570	83,570
Y-Mean	2.9	3.2

	B: Staff Per Patient Day			
	(1) All Staff	(2) Nurse Assistant	(3) Licensed Nurse	(4) Registered Nurse
Overall				
1(PE)	-0.0332***	-0.0714***	-0.0269***	0.0599***
	(0.013)	(0.009)	(0.004)	(0.003)
Never PE vs. Timing				
1(PE)	-0.0347	-0.0733	-0.0273	0.0606
Weight	0.98	0.98	0.98	0.98
Always PE vs. Timing				
1(PE)	0.1304	0.0347	-0.0609	0.1773
Weight	0.00	0.00	0.00	0.00
Observations	181,220	181,220	181,220	181,220
Y-Mean	3.6	2.3	0.8	0.5

	C: Log Financials		
	(1) Management Fee	(2) Building Lease	(3) Interest Expense
Overall			
1(PE)	0.8275***	0.3711***	1.0093***
	(0.019)	(0.028)	(0.025)
Never PE vs. Timing			
1(PE)	0.8389	0.3730	1.0184
Weight	0.98	0.98	0.98
Always PE vs. Timing			
1(PE)	0.9580	0.9299	2.8145
Weight	0.00	0.00	0.00
Observations	153,510	153,522	153,539
Y-Mean	0.2	0.4	0.3

Note: This table presents heterogeneity in component estimates for our key aggregate outcomes obtained by following Goodman-Bacon (2021) and using the main specification (Equation 10). The corresponding main results are presented Table 8. For this analysis we had to limit the sample to ensure a balanced panel, which affected the overall estimates slightly. Each cell presents the coefficient β obtained by estimating Equation (10) with a different outcome. The independent variable is an indicator for whether a nursing home is PE-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. We show the overall effect in the first row, the coefficient and weight of Never PE vs. staggered PE indicator in the second row, and the coefficient and weight for Always PE vs staggered PE indicator in the third row. All variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.

Table C.10: **Patient Volume**

	Facility Level		Market Level
	(1) Log Beds	(2) Log Admissions	(3) Log Admissions
1(PE)	-0.002	0.036***	0.014
(No Control)	(0.003)	(0.009)	(0.014)
1(PE)	-0.003	0.035***	0.007
(With Control)	(0.003)	(0.009)	(0.011)
Observations	283,767	283,767	5,364
Y-Mean	4.5	4.8	12.7

Note: This table presents estimates of the relationship between PE ownership and patient volume. Each cell presents the coefficient β obtained by estimating Equation (10) with a different outcome. The independent variable is an indicator for whether a nursing home is PE-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. We present results on the log number of beds, log number of admissions in facility, and log number of admissions at HRR level. The bottom row presents the results including controls, which consist of market-level and patient mix controls, as described in Section 6.1. All models include facility and year fixed effects. All variables are winsorized at 1% and 99% levels. Standard errors are clustered by facility.