Does Private Equity Investment in Healthcare Benefit Patients? Evidence from Nursing Homes*

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Abstract

The past two decades have seen a rapid increase in private equity (PE) investment in healthcare, a sector in which intensive government subsidy and market frictions could lead high-powered for-profit incentives to be misaligned with the social goal of affordable, quality care. This paper studies the effects of PE ownership on patient welfare at nursing homes. With administrative patient-level data, we use a within-facility differences-in-differences design to address non-random targeting of facilities. We use distance as an instrument to control for the selection of patients into nursing homes. Our estimates show that PE ownership increases the short-term mortality of Medicare patients by 13%, implying 28,000 lives lost due to PE ownership over our twelve-year sample period. This is accompanied by declines in other measures of patient well-being, such as lower mobility, while taxpayer spending per patient episode increases by 11%. We observe multiple clinical and operational changes that help explain these effects, including declines in nursing staff and compliance with standards. Finally, we document a systematic shift in operating costs post-acquisition toward non-patient care items such as monitoring fees, interest, and lease payments.

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1 Introduction

The U.S. spends more than other developed countries on healthcare, yet has worse health outcomes (Garber and Skinner, 2008). Private equity (PE) ownership might address these challenges because it has been shown to increase productivity in industries such as manufacturing and restaurants (Kaplan, 1989; Davis et al., 2014; Bloom et al., 2015b; Bernstein and Sheen, 2016).[1] However, the healthcare sector has high levels of government subsidy, which can weaken the natural ability of a market to align firm incentives with consumer welfare (Cutler, 2011; Skinner, 2011). Further, since quality is not fully contractible and information frictions prevail, the high-powered incentives to maximize profits that characterize PE ownership could have detrimental implications for patients and taxpayers (Hansmann, 1980; Hart et al., 1997; Chandra et al., 2016).

This tradeoff between PE's possible efficiency gains and the scope for actions that increase profitability but adversely affect patients, coupled with a rapid rise in PE ownership in healthcare, has attracted significant attention from policymakers. For example, 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," while a member of the British Parliament argued that PE-owned nursing homes in the UK pursue "profiteering, cost and corner cutting, all the while their owners are loading them up on debt with high interest rates and expecting the taxpayer to pay when it fails" (Brown et al., 2019; Hodgson, 2020).[2] Meanwhile, voices from the private sector often paint a different picture; 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" (Saenz, 2019).

This debate has come to the fore because of rising PE activity in U.S. healthcare over the

[1] PE ownership can affect firm performance because it confers distinct incentives to quickly and substantially increase firm value. See Section 2.2 for an explanation of PE and its incentive structure.

[2] Policymaker concern has focused not only on nursing home quality (Doggett et al., 2020), but also surprise medical bills (Cooper et al., 2020) and predatory acquisitions of physician practices (King, 2020), among other areas. Also see Flood (2019) and Lewis (2019).

last two decades, with total investment increasing from less than $5 billion in 2000 to more than $100 billion in 2018 (Appelbaum and Batt, 2020). PE-owned firms provide the staffing for more than one-third of emergency rooms, own large hospital and nursing home chains, and are rapidly expanding ownership of physician practices.[3] Thus far, evidence to inform the animated policy discussion is inconclusive.

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; the average nursing home receives 75% of revenue from the government, and 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 in isolating the effects of PE ownership from the related phenomenon of corporatization in medical care (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 18,485 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. The rich data enables us to estimate the impact on Medicare, which accounts for about 60% of the unique patients that enter a nursing home during our sample period, even though it covers a small fraction of patient days.

There are two empirical challenges to estimating the causal effects of PE ownership. The first is non-random selection of acquisition targets. To partly address this, we include facility fixed effects in our specifications. This eliminates time invariant differences across facilities and their local markets. We also include patient market by year fixed effects, effectively comparing outcomes within patients that originate in the same market and year. This mitigates concerns about unobserved differential trends in market structure across locations. Finally, we present event studies and assess pre-trends for all outcomes.

[3] See Bruch et al. (2020); Brown et al. (2020); Casalino (2020).

The second challenge is to overcome unobserved changes in patient composition following PE ownership. Medicare adjusts nursing home payments for observed measures of patient risk to compensate facilities for greater costs involved in serving more complex patients. At the same time, among patients with similar risk as observed by Medicare, less complex patients entail lower costs. Thus, nursing homes can increase profits by selecting unobservedly less risky patients. This predicts little change in aggregate measures of risk, but a decline in unobserved patient risk. Consistent with this conjecture, following PE buyouts we find no change in the Charlson score, a standard claims-based measure which aggregates information across multiple co-morbidities, but do find declines in measures associated with high nursing home costs such as cognitive impairments and the ability to perform daily activities (Hackmann, Pohl and Ziebarth (2018)). 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, allowing us to overcome patient selection. We assess instrument validity using multiple tests and find reassuring evidence.

Using this IV strategy embedded into the differences-in-differences model, we examine the effects of PE buyouts on patient welfare. The most important and objective measure in our context is short-term survival (McClellan and Staiger, 1999). We find that going to a PE-owned nursing home increases the probability of death during the stay and the following 90 days by 2.4 percentage points, about 14% of the mean. The mortality effect is detectable as early as 15 days following discharge and is remarkably stable as a share of the mean regardless of the duration studied. Applying the local average treatment effect (LATE) to all patients served by PE owned facilities in our sample implies 28,000 Medicare lives lost due to PE ownership of nursing homes. In turn, this corresponds to about 214,000 life-years lost, based on the observed age and gender distribution of Medicare decedents. Using a conventional value of a life-year from the literature, this estimate implies a mortality cost of about $28 billion in 2016 dollars. To put this in perspective, this is about two times

the total payment made by Medicare to PE facilities during our sample period. Juxtaposed against this decline in quality, we find an 11% increase in the amount billed to Medicare per stay. Taken together, these results suggest that PE ownership decreases nursing home productivity, as measured by our proxies for quality purchased per dollar.

These results are robust when subjected to a battery of specification tests. Reassuringly, the effect does not appear in a placebo analysis testing for pre-buyout effects. Furthermore, we find similar worsening in other commonly used measures of nursing home quality, such as patient mobility and pain intensity. We find that going to a PE-owned nursing home increases the probability of taking antipsychotic medications – discouraged in the elderly due to their association with greater mortality – by one-third. We also assess whether the results are driven by the related, but distinct phenomenon of corporatization. However, 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 next consider nurse availability, which is the most important determinant of quality of care (Zhang and Grabowski, 2004; Lin, 2014). We find that 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 and ensure sanitary conditions. The loss of front-line staff is most problematic for less complex patients. Elevated antipsychotic use could also be partly explained as a substitution response to lower nurse availability (Cawley et al., 2006). We can explain about a quarter of the mortality effect using previously published mortality effects of antipsychotic use and lower nurse availability, assuming these factors are additive (Schneider et al., 2005; Tong, 2011). However, this may be an understatement if these factors are more harmful when they interact. We also find negative effects on facility Five Star ratings, which are constructed by CMS to provide summary information on quality of care.[4]

[4]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, in particular CMS' Five Star Ratings (Grabowski and Town, 2011; Werner et al., 2012).

Taken together, our results suggest that PE-owned nursing homes select unobservedly less risky patients. We show that on dimensions associated with costly care, there are clear declines in risk, such as cognitive impairments and activities of daily living. Consistent with lower unobservable risk, the OLS estimates are smaller. Among high-risk cohorts, PE-owned nursing homes appear to maintain quality, even increasing the number of RNs who are responsible for the most medicalized aspects of treatment. However, the average patient suffers, driven by lower availability of frontline nurses and decline in compliance with quality standards, while keeping low-risk patients longer to maximize Medicare revenue. Consistent with these patterns, we find that low-risk patients disproportionately drive the mortality effect.

To formally assess the external validity of the LATE, we estimate marginal treatment effects (MTE) and recover an average treatment effect (ATE) of about 0.9 pp. Hence, the conclusion that patients are worse off at PE-owned facilities can be generalized beyond distance compliers to the average Medicare patient. However, the MTE analysis also reveals substantial heterogeneity in treatment effects, including negative MTE values (i.e., a beneficial effect) for some types of patients.

Finally, we assess facility finances to shed light on how the financial strategies particular to the PE industry affect operations. A puzzle is why nursing homes are attractive targets 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, raising the question of how PE firms create value. 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, these elements that we are able to analyze shed light on changing financial strategies.

This paper contributes to three strands of the literature. First, we provide new evidence on the effects of PE ownership on target firm operations (Boucly et al., 2011), product quality (Lerner et al., 2011; Fracassi et al., 2020), and value (Gupta and Van Nieuwerburgh, 2019; Bernstein et al., 2019; Biesinger et al., 2020). We overcome most limitations of previous studies on PE in healthcare, such as limited geographies, a short sample period, a lack of patient-level data, or a small number of deals (Stevenson and Grabowski, 2008; 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). To our knowledge, no national study on PE or on ownership in healthcare has simultaneously addressed both facility-level and patient-level selection.

Second, this paper adds to the literature on how provider ownership interacts with price incentives and regulation in healthcare Duggan (2000); Grabowski and Hirth (2003); Grabowski et al. (2013); Clemens and Gottlieb (2014); Adelino et al. (2015); Hill et al. (2019); Curto et al. (2019).[5] Some work points to non-pecuniary objectives of nonprofits as one reason nonprofit providers can outperform for-profits. Our results appear consistent with this theme, potentially raising questions about whether antitrust regulators should prospectively review PE deals in healthcare.[6]

Third, this paper contributes to the emerging literature on the industrial organization of the nursing home sector, which has received less attention than hospitals in economics (Lin, 2015; Hackmann et al., 2018; Hackmann, 2019). Previous work has focused on the role of competition and payment rates in determining quality. Our results imply that owner incentives are of first-order importance, which may be helpful for policymakers as they consider regulatory actions to improve transparency and accountability. For example, in light of prior work showing how PE increases performance when incentives between

[5]There is also a related literature on competition in healthcare markets Bloom et al. (2015a), Curto et al. (2021); Grabowski and Hirth (2003); Dafny et al. (2012); Cooper et al. (2018); Pelech (2018); Ho and Lee (2019).

[6]The largest deals in our sample involved purchases of nursing home chains owning hundreds of facilities already and which remained stable in size. Both the US House and Senate are considering expanding the scope of the prevailing anti-trust laws. As example, see https://www.cnbc.com/2021/02/04/klobuchar-unveils-sweeping-antitrust-bill-laying-out-her-vision-as-new-subcommittee-chair-.html.

investors and consumers are well-aligned, government reimbursements targeting outcomes could potentially improve patient welfare. These issues have become more urgent as the COVID-19 pandemic has exposed flaws in the regulation and financing of long-term care facilities, which have accounted for nearly 40% of U.S. deaths from the virus.[7]

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).[8] 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).[9]

As with any business, the economics of nursing homes are shaped by the nature of

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

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

[9]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).

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 well-functioning market. These rates are non-negotiable, and facilities simply choose whether they will accept 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.[10] Overall profit margins are in the low single digits (MedPAC, 2017), a topic we return to at the end of the paper. Payments are adjusted for patient complexity, so there is an incentive to overstate their severity—a practice known as 'up-coding.' This makes it difficult to use risk as an outcome.

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). Staffing ratios are therefore standard metrics to examine nursing home quality (Hackmann, 2019).

Economists have long emphasized the importance of information asymmetry between patients and healthcare providers (McGuire, 2000). It is difficult for patients to assess

[10] 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.

nursing home quality and compare it to available alternatives, and as discussed above, price is not a helpful quality signal in this setting. Reputation is therefore likely to have an unusually large influence on demand for nursing homes (Arrow, 1963). Profit maximizing facilities should optimally invest in building and sustaining their reputation. This creates a dynamic incentive problem where they could generate higher profits in the short-term by cutting patient care costs (nursing staff, for example), but they may optimally sacrifice these short-term profits in order to maintain their reputation and safeguard patient demand for the long-term. It remains unclear which factor inputs affect nursing home reputation, but evidence from prior studies suggests that patient demand does not respond to poor quality scores on government mandated report cards (Grabowski and Town, 2011; Werner et al., 2012).

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.[11] PE is associated with particularly high-powered incentives to maximize profits because fund managers are compensated through a call option-like share of the profits, employ large amounts of leverage collateralized with target firm assets, aim to liquidate investments within a short time frame, and do not have existing relationships with target firm stakeholders (Kaplan and Stromberg, 2009). Specifically, the compensation of the General Partners (GPs) who manage PE funds stems primarily 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 typically receive 20% of profits after a hurdle rate, which the fund's investors (Limited Partners) are guaranteed before GPs receive any profits. GPs also receive transaction and monitoring fees, which are not tied to performance. Overall, however, PE managers typically do not earn returns if the business continues as-is, motivating aggressive value-creation strategies. In contrast, a traditional

[11] 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.

business owner running the firm as a long-term going concern with a lower debt burden may prefer lower but more stable profits.

A large literature in finance beginning with Kaplan (1989) and Kaplan and Schoar (2005) has shown that in part due to the call option-like nature of GP compensation, PE buyouts increase productivity, operational efficiency, and generate higher returns. 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 the alleviation of credit constraints (Boucly et al., 2011), which may lead to increases in investment and improved operations, and exploiting the favorable tax code treatment of debt financing (Spaenjers and Steiner, 2020), which may increase financial stress and the chances of default.

Governance engineering includes a number of 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, in addition to frequently changing key managers, PE owners also increase the equity stake of the management team and introduce performance-based compensation (Gompers et al., 2016). Bloom et al. (2015b) show that PE-owned firms are better managed than similar firms that are not PE-owned.

Operations engineering refers to the more recent practice of PE firms applying their industry expertise to add value to their investments. PE owners identify both strategic and operational opportunities, such as re-branding, organization restructuring, investing in new technology, expanding to new markets, and cost-cutting (Gadiesh and MacArthur, 2008; Acharya et al., 2013; Bernstein and Sheen, 2016). Davis et al. (2014) show that PE buyouts are linked to greater labor churn, the expansion of efficient operations and the closure of inefficient operations.

Considering these changes in the context of nursing homes, the effects 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. The first is that cost cutting measures and a focus on capturing subsidies could come at the expense of quality improvement efforts. The second is that

the nursing home incurs a large debt obligation as part of the buyout, and the resulting interest payments can reduce the cash available for care. A related additional cost is leasing property that formerly was owned by the nursing home. PE owners often sell real estate assets shortly after the buyout, which generates cash that can be returned to investors. 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).

Finally, the third force is the relatively short-term time horizon of PE investments, which could push managers to focus on maximizing short-term profits even if they come at the expense of long term reputation and 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 obtained 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. The ratings first appear in 2009. Fortunately, 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) to obtain additional clinical insights. These data are confidential and were accessed under a data use agreement with CMS. They include patient enrollment details, demographics, mortality, and information about care in nursing homes and hospitals during this period.

In patient-level analysis, 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. 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). 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 the entire cost until the 21^{st} day of stay, at which point the patient begins paying a coinsurance. Consequently, about 90% of total payments in our data are made by Medicare and patients bear the remainder. We complement the mortality analysis by examining some ancillary measures of patient

well-being using the clinical assessments. We study four outcomes that CMS uses when computing the Five Star quality ratings for nursing homes. The first is an indicator for the use of antipsychotic medication during the stay. Antipsychotic use in the elderly is known to increase mortality, and non-pharmaceutical interventions such as music and breathing exercises have been shown to be more effective (Taragano et al., 1997; Kuehn, 2005; Sink et al., 2005; Schneider et al., 2005; Banerjee et al., 2011; Press and Alexander, 2013). The second is an indicator for the patient's self-reported mobility score declining during the stay. The third is an indicator for developing a pressure ulcer. The fourth 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 B.1 shows the number of deals in each year; the deals are spread over time, and no part of the business cycle dominates. The deals are also spread across PE firms. In total, our data contain 136 unique PE firms that acquired nursing homes. Most deals are syndicated and involve multiple PE firms. Table B.1 presents the top 10 deals by number of facilities acquired. On average, we observe PE-owned facilities for eight years post-acquisition. Hence the results should be interpreted as medium to long-term effects of PE ownership. 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). The PE investors in our sample include very large funds, smaller funds, and specialized healthcare

PE investment funds. PE firms which account for the greatest number of deals are Onex, Fillmore Capital Partners, The Hillview Group, The Carlyle Group, Cammeby International, Heritage Partners, Lydian Capital, Formation Capital, and Oaktree.

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 used in the analysis 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 standards from regulators over time. As the PE deals occurred primarily later in the sample, it is therefore remarkable that they have lower measures of quality on average. Panel B shows that demographic measures are similar across the types of facilities, such as patient age and a high-risk indicator.[12] PE-owned facilities bill about 10% more per stay than non-PE facilities. Figure 7 panel A

[12]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.

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. Since Medicare does not pay for stays longer than 100 days, we limit our sample to patients staying within this threshold.

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.[13] County-level income, race, and home ownership do not predict buyouts. 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 variation within patients that originate in the same market in the same year. Second, following a PE buyout, the composition of patients may 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 complex or costly to serve patients (Gandhi, 2020). Hackmann, Pohl and Ziebarth (2018) find that

[13]The map in Figure B.2 shows that deals are not excessively concentrated in particular areas of the country.

patients with cognitive impairments and who need help with more activities of daily living (ADL) are the most expensive to serve. We find evidence of reductions in patient risk following PE ownership in our data. Table 4 Panel A presents point estimates from differences-in-differences models that exploit variation in the timing of the PE deals across facilities. 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 B.4 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 if there is a similar decline in unobserved patient risk following PE ownership, it will bias mortality and spending effects toward zero. Therefore, we develop an instrument for the match between patients and nursing homes.

4.1 Distance-based Instrument

We use a differential distance instrument (McClellan et al., 1994) to control for endogenous patient selection into nursing homes. The instrument 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. This is also evident 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 B.5).[14] As a result of these patterns, this instrument has been used to control for patient selection into nursing homes (Grabowski et al., 2013; Huang and Bowblis, 2019).

We compute the difference (in miles) between two distances: from a patient's home

[14]Distance patterns remain remarkably stable over time in our sample. Mean distance to facility is unaffected by PE buyout, as shown in Figure B.5D.

zip code to the closest PE-owned facility zip code; and from the patient's residence to the nearest non-PE facility zip code. A positive value indicates the patient is closer to a non-PE facility. A lower differential distance value implies the nearest PE-owned facility is closer to the patient. 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.[15] Besides following convention, this approach has two benefits. First, the sample is limited to patients living in markets plausibly targeted by PE firms and is therefore more homogeneous. Second, this improves instrument power since patients in the excluded zip codes are infra-marginal and their facility choice is not sensitive to changes in differential distance.

The first stage is estimated using Equation (1), and the second stage is estimated using Equation (2). The endogenous regressor of interest $PE_{i,j,r,t}$ is an indicator set to one if patient i in Hospital Referral Region (HRR) r chooses PE-owned facility j in year t. 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 began, t.

$$PE_{i,j,r,t} = \alpha_j + \alpha_{r,t} + \zeta_1 D_i + \zeta_2 D_i^2 + X'_{i,z}\,\xi + \nu_{i,j,r,t} \tag{1}$$

$$Y_{i,j,r,t} = \alpha_j + \alpha_{r,t} + \phi\, PE_{i,j,r,t} + X'_{i,z}\,\gamma + \varepsilon_{i,j,r,t} \tag{2}$$

Our preferred model controls for facility, α_j, and patient HRR by year fixed effects, $\alpha_{r,t}$. The vector $X_{i,z}$ denotes patient risk controls including age, indicators for gender, marital status, dual eligible, and 17 disease categories.[16] We conduct multiple robustness checks, which include adding time-varying socioeconomic variables at the patient's zipcode-year level and omitting all controls.[17] Standard errors are clustered by facility to account for unobserved

[15] 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 throughout our sample period.

[16] To construct these indicators, we use diagnoses codes recorded in claims billed over the three months prior to the index nursing home stay (hospital stays, ED visits, and outpatient visits).

[17] 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

correlation in outcomes across patients treated at the same nursing home.

The instrument is strongly predictive of choice of nursing home type. The first stage results are reported in Table 2. 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.

4.2 Instrument Assumptions and Validation Tests

IV estimation differs from randomized controlled trials because the randomization of patients to treatment is indirect rather than deliberate. As in all such analyses, we must rely on two untestable identification assumptions. The first is conditional random assignment, which requires that after conditioning on covariates, unobserved characteristics correlated with the outcomes of interest are not correlated with differential distance. This assumption subsumes the exclusion restriction, that the patient's differential distance to a PE facility affects outcomes only by influencing her probability of being treated at a PE facility. The second assumption is monotonicity, which assumes that a decrease in 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).

We now discuss several pieces of evidence to support the plausibility of the above assumptions. A common check to support conditional randomization is to test for correlation between the instrument and patient observables, particularly covariates which may affect mortality, such as risk. Figure 2 Panel A visually presents the relationship between patient risk and the instrument and indicates little or no correlation.[18] Formally, the figure implies that the probability of being a high-risk patient (Charlson score $>$ 2)

below the Federal poverty line.

[18]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.

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 2 columns 1 and 2 show that the coefficients on differential distance are nearly unaffected by including patient-level controls, corroborating this interpretation.

Additional evidence for random assignment is that characteristics are similar for patients with above- and below-median values of differential distance. We document this in Table 3, where we summarize 21 patient characteristics for the two groups. 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, and about a quarter of the patients in both groups have diabetes. While differential distance is highly predictive of going to a PE-owned facility, it appears to randomize patients with respect to demographics and co-morbidities. We note that the instrument also appears to balance patients on the same measures of cognitive impairments and ADLs discussed previously where we found a decline post-buyout.

PE firms may strategically target more lucrative zip codes within an HRR, where the patients may be sicker with higher expected mortality. Patients in such neighborhoods could be located closer to a PE facility, therefore face a negative differential distance and a higher mortality rate— a violation of the exclusion restriction. Since HRRs are large and encompass dozens of neighborhoods, this is a plausible concern. We perform multiple tests to assess the importance of this concern. We replicate our models using the more granular market definition of Hospital Service Areas (HSA). There are nearly 3,400 HSAs, while there are only about 300 HRRs. Table 2 column 4 presents results using this market definition and finds similar patterns. In Section 5.1 we show that the effects on mortality and spending remain large and statistically significant if we use HSAs to define markets. Next, we perform two falsification checks to test for spurious effects on the outcomes of interest. Since these tests involve modeling the outcomes as well, we discuss these after first presenting the main results on mortality and spending.

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 2. We flexibly allow HRRs to evolve on different trends to mitigate the possibility of differences in market structure confounding our results.

We provide evidence consistent with the monotonicity assumption in Figure 2 Panel B, which 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 monotonicity assumption also implies that the first stage should be negative when estimated on sub-samples of patients with different characteristics. Table B.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.

Table B.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.[19] Compliers appear to have a very similar age distribution and the probability of being male, married, or white. Intuitively, distance-based compliers are slightly more likely to be from a low-income zipcode.

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

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

The main IV results are reported in Table 4 Panel B. These estimates use Equation (2) and include 22 patient-level controls (described in Section 4.1), facility fixed effects, and patient HRR-by-year fixed effects. Column 1 indicates that receiving care at a PE-owned nursing home increases the probability of death during the stay and the following 90 days by 2.4 pp, about 13% of the mean. (Alternative durations and controls are discussed in the robustness section below.) In the context of the health economics literature, this is a very large effect.

The next two columns of Table 4 Panel A consider spending per patient. In our data, more than 90% of the billed amount is paid by taxpayers through Medicare and patients pay the balance. The amount billed per nursing home stay increases by 11% (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. This does not seem to reflect additional preventive care that is compensated for by lower subsequent needs, because the total amount billed for both the stay and the 90 days following the stay (the episode) increases by 8.5%.

The IV estimates imply that the reduced form effect on mortality and spending should decline as differential distance grows larger (i.e., relative to the nearest alternative, a PE facility is farther away). Figure 3 provides non-parametric evidence to confirm this pattern. This figure is produced using the same approach as in Figure 2, except that the variables plotted on the y-axes are the outcomes of interest. 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 B.3 Panel A. The

IV coefficients are mapped to lives and life-years lost based on the number of index stays by patients of 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.[20] Applying a standard estimate of statistical value of a life-year of $100,000 (Cutler and McClellan, 2001) inflated to 2016 dollars, this implies a mortality cost of $27.8 billion.

Robustness Tests

We present results from a battery of specification and falsification checks to address 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 randomly set the PE dummy to turn on in 2004 or 2005 for facilities that eventually were acquired by PE firms later. 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 4 Panel C presents these placebo estimates and reassuringly finds small and insignificant effects, implying a lack of differential trends prior to acquisition.

In another falsification check, 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

[20] 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.

facilities (within one mile) are unlikely to choose based on this differential. Table B.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 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 B.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.

Alternative Explanations

Most patients in our sample enter the nursing home immediately following a hospital stay. However, our main models do not incorporate the discharge decision at the hospital. A potential concern here is that PE firms may also acquire hospitals and influence the decision to send patients to nursing homes. For example, they may encourage hospitals to send more patients for SNF care. To assess the importance of this concern we study the effects of PE entry into a market on hospital discharge decisions to nursing homes. Table B.6 Panel A presents from OLS estimation of patient-level models where the outcome is probability of being discharged to a nursing home. We estimate these models using different market definitions (HRR and HSA). Regardless of the definition, we find that PE entry into a market does not appear to change hospital referral decisions on the extensive margin.

An alternative interpretation of these results is that PE ownership could bring economies of scale or corporatization, which are the explanation that Eliason et al. (2020) propose for 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 also 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 specific firms such as Formation Capital and Filmore Capital which may be unrepresentative of the average PE firm (row 7.B).

Another concern is whether the results primarily reflect a quality difference between for-profit and nonprofit nursing facilities. About 20% of patients in our sample receive treatment at non-profit facilities, which are in the comparison group. We test the sensitivity of our main estimate to excluding these facilities from the sample altogether. The estimates decline slightly in magnitude but remain qualitatively similar (row 8).

OLS Results and Patient Risk

OLS results are presented in Table 4 Panel D. There is a statistically significant, but much smaller increase in mortality in the OLS model (0.3 pp, column 1). In a similar vein, we find small, negative effects on spending of 1-2% (columns 2-3). The corresponding event studies, in Figure B.3, suggest no pre-trends, consistent with the parallel trends assumption that underlies our empirical model (i.e., target facilities and control facilities would continue on parallel trends in the absence of the buyout). This pattern of OLS estimates being closer to zero is consistent with our concern about unobserved selection of patients based on complexity, also indicated by the decline in ADL scores and cognitive impairments (see Figure B.4).

5.2 Heterogeneity in the Mortality Effect

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

5.2.1 Observed attributes

To assess heterogeneity in the IV analysis, we split the sample based on observed characteristics. Table 6 presents the corresponding results. We also present the mean mortality rates for each sub-group to help interpret the magnitudes. We first consider risk.

Higher risk – a measure constructed from disease burdens – should be associated with more need for high-skill, medicalized RN care. Lower risk patients might be more sensitive to changes attentive but not necessarily high-skill or complex care, for example helping patients to use the toilet and minimizing infection risk. Therefore, we split the sample into two groups around the high-risk indicator (Charlson score above two). This measure clearly isolates patients with higher mortality rates (29% vs. 14%). The results, shown in Table 6 row 1, indicate that relative to the mean mortality rate, lower risk patients experience a much greater increase in mortality (19% vs. 7%).

We next consider gender in row 2. We find similar results among both men and women, and both are statistically significant despite female patients accounting for 64% of the sample and being on average older. Third, we divide the sample at the median length of stay. Since length of stay itself may be affected by PE ownership, this analysis does not necessarily imply a causal effect of length on mortality, but hints at a mechanism. The mortality effect is driven primarily by patients with below median stays; for this group, the effect is very large at 4.1 pp, while it is insignificant and much smaller (1.3 pp) for above-median stay patients. This is consistent with the previous result that lower risk patients experience worse mortality effects. It also contradicts a potential concern that PE facilities may be appearing worse on mortality due to sicker patients who need a long time to recover, but are more likely to die subsequently.

We explore this further by studying the impact of PE ownership on length of stay at different values throughout the distribution. The goal is to identify whether certain types of stays particularly experience an increase in duration. 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 7 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. However, the figure also implies little or no effect on stays becoming longer than 35 or more days. In other words, PE facilities keep very short stayers longer. This appears to be maximizing Medicare payments, which pays

fully for the first 20 days of SNF stays, but then tapers off. If we tie this to the mortality analysis discussed above, it appears that extending the short stays may play an important role in elevating mortality.[21]

Table 6 row 4 examines mortality effects for patients discharged to different destinations. The mortality effect is driven entirely by patients discharged to facility, a group mainly composed of patients sent to hospitals. Note that we do not find changes in the proportion of patients sent to the different destinations (see Table B.6 panel B). However, there could be changes in the composition of patients sent to different locations, hence these results do not necessarily reflect causal effects. To explore these effects further, in row 5 we disaggregate patients discharged to hospitals by the category of the reason for hospitalization. We find the greatest effect for patients admitted with an injury or infection.

5.2.2 MTE Theory and Estimation Approach

The LATE may mask treatment effect heterogeneity across different types of patients. For example, some patients may benefit from the type of care that is offered by PE-owned facilities, even though we estimated negative impacts on average for the complier group. It also ignores the possibility of patient selection on treatment gains. The MTE framework allows us to examine these dimensions (Heckman and Vytlacil, 2005; Heckman et al., 2006). It enables us to compute treatment effect parameters of economic interest such as the Average Treatment Effect (ATE) and Treatment on the Treated (ATT). Unlike the LATE, these parameters are not specific to the complier group and allow us to make more general statements regarding the causal effects of PE ownership.

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

[21] 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.

unobserved factors.[22]

$$Y_{k,i} = X_i' \beta_k + F_j + R_{r,t} + U_{k,i}, \quad k = 0, 1 \tag{3}$$

We then propose a latent selection model of how patients choose a PE-owned facility based on observed and unobserved factors.

$$\begin{aligned} PE_i^* &= Z_i'\delta - V_i, \\ PE_i &= 1 \; if \; PE_i^* \geq 0, \; PE_i = 0 \quad \text{otherwise}, \end{aligned} \tag{4}$$

where $Z = (X, F, R, D, D^2)$ is a vector including all the controls listed above in Equation (3) 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:

$$Z_i'\delta - V_i \geq 0 \implies Z_i'\delta \geq V_i \implies \Phi(Z_i'\delta) \geq \Phi(V_i), \tag{5}$$

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, the MTE is defined as $MTE(X = x, U_D = u) = \mathbb{E}[Y_1 - Y_0 | X = x, U_D = u]$. 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 an observed and unobserved component. This allows the MTE to be identified over the unconditional support of $P(Z)$ across all values of X rather than the support of $P(Z)$ conditional on $X = x$, easing the burden of identifying variation needed from the data (Carneiro et al., 2011).

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

$$
\begin{aligned}
MTE(X = x, U_D = u) &= \mathbb{E}[Y_1 - Y_0 | X = x, U_D = u] \\
&= \underbrace{x(\beta_1 - \beta_0)}_{observed} \quad + \quad \underbrace{\mathbb{E}[U_1 - U_0 | U_D = u]}_{unobserved}
\end{aligned} \tag{6}
$$

Another implication of this assumption is that treatment effect heterogeneity due to X affects the MTE curve in u only through the intercept. The slope of the MTE curve in u does not depend on X, facilitating estimation. The potential outcomes model described above produces the following outcome equation as a function of observables and $P(Z)$ (Carneiro et al., 2011).

$$
\mathbb{E}[Y | X, F, R, P(Z) = p] = X'\beta_0 + F + R + X'(\beta_1 - \beta_0)p + K(p), \tag{7}
$$

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 first estimate the selection model in Equation (4) using a linear probability model and obtain $\hat{p} = Z'\hat{\delta}$. Figure 4 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 2—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 4 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.[23] We then estimate the outcome Equation (8) below, assuming $K(p)$ is a polynomial in p of degree S.

$$
Y = X'\beta_0 + F + R + X'(\beta_1 - \beta_0)\hat{p} + \sum_{s=2}^{S} \rho_s K(\hat{p}) + \epsilon. \tag{8}
$$

[23] We have atleast 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.

The MTE curve is the derivative of Equation (8) with respect to $\hat{p}$. In our baseline model we set $S = 2$, but test robustness to using higher order polynomials. Standard errors are obtained by block bootstrap, clustering by facility.

5.2.3 MTE Results

We estimate Equation (8) 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 4 Panel C presents the MTE curve along with 90% confidence intervals. Our primary approach uses a second degree polynomial, so the MTE curve is linear in unobserved resistance (u). Since it is downward sloping, it 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). Figure B.6 panel A provides a reassuring 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 very 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 B.6 Panel B shows that the curve remains downward sloping regardless of the polynomial.

We aggregate the marginal treatment effects using the appropriate weights to obtain various treatment effect parameters such as the unconditional ATE and ATT (Cornelissen et al., 2016). Given the downward sloping nature of the MTE curve, we expect the average effect on the treated to be higher than that for the untreated. Figure 4 Panel D presents the weights to apply to the MTE values to compute the ATT and ATUT. Accordingly, 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.

There are two key takeaways from this analysis. First, the ATE implies that a randomly

chosen Medicare patient from our sample would experience an increase of 0.9 pp in the probability of short-term mortality if she goes to a PE-owned nursing home. While significantly lower than the LATE estimate, it nevertheless 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.

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. Therefore, we also use the IV model to assess effects on the four clinical measures of wellbeing that CMS uses as outcomes for short-stays when computing Five Star ratings (surprisingly, mortality is not one of them). The first is whether a patient starts taking antipsychotic drugs. As discussed in Section 3, antipsychotics are discouraged in the elderly due to their association with mortality and the greater efficacy of behavioral interventions. We find that going to a PE-owned nursing home increases the chances of starting antipsychotics by 3 pp, or one-third of the mean (Table 7 column 1). Using an estimate from the literature on how antipsychotic medications affect mortality, this coefficient implies that about 10% of the total effect on mortality is potentially attributable to starting antipsychotics.[24]

We also find a positive effect on experiencing worsening mobility, which increases by 2 pp, or about 4% of the mean (Table 7 column 2). We do not find a significant effect on the third measure – developing ulcers. Fourth, there is a positive effect on increasing pain

[24]Several clinical studies have examined the harmful effects of antipsychotic prescribing for the elderly. The most relevant study for our purposes is by Schneider et al. (2005), who perform a meta-analysis of fifteen randomized controlled trials (11 from nursing homes) that studied the effects of antipsychotics on mortality for elderly patients. They report a 50% increase in mortality. The trials evaluated mortality at durations averaging about 3 months, coincidentally matching our mortality measure. Applying a 50% increase in mortality to our setting implies an 9 pp increase in 90-day mortality on a mean of 18 pp. We apply this elevated mortality effect to the 3 percent additional patients at PE facilities who receive antipsychotics. This implies an increase in mortality of 9 x 0.03 = 0.27 pp for PE patients on average.

intensity of 3.4 pp, which is 12% of the mean. Figure B.3 presents the corresponding event studies and indicate no differential pre-trends. Overall, the evidence of harmful effects on other measures of patient wellbeing are comfortingly consistent with the estimated effects on mortality.

6 Operational Changes

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

6.1 Empirical Strategy

For outcomes available only at the nursing home level, we cannot instrument for patient selection and the best possible research design therefore is differences-in-differences. We use variants of the following specification:

$$Y_{j,t} = \alpha_j + \alpha_t + \beta PE_{j,t} + P'_{j,t}\gamma_1 + M'_{j,t}\gamma_2 + \varepsilon_{j,t} \tag{9}$$

$PE_{j,t}$ 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.[25] 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

[25]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.

parallel trends in the absence of the acquisition. We assess whether there are differential pre-trends using event study figures, which plot the coefficients β_s from estimating Equation (10) below.

$$Y_{j,t} = \alpha_j + \alpha_t + \sum_{s \neq 0} \beta_s \text{Deal Year}_{\text{j,s}} + P'_{j,t}\,\gamma_1 + M'_{j,t}\,\gamma_2 + \varepsilon_{j,t} \tag{10}$$

$\text{Deal Year}_{\text{j,s}}$ 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 (9).

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 5 and 6.

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 5 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.[26]

[26]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.

In 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 aggregate effect 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. 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 5 again reveal no pre-trends and indicate more immediate declines after the deal in front-line staffing, while the increase in RN staffing appears starting 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 are taking 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, including only for-profit nursing homes (Table B.7). The coefficients remain largely unaffected due to these checks. Following Goodman-Bacon (2021), we decompose the D-D estimate into different components and find that more than 90% of the weight is on the effect obtained by comparing treated facilities with never-treated facilities (Table B.8).

The existing literature helps to connect the effects on nurse availability with the estimated effect on mortality. 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. Applying her estimates in our setting, the estimated decline in frontline nurse staffing predicts an increase in mortality of 0.25 pp.[27] The findings on increased use of antipsychotics and lower nurse availability may be related. Grabowski et

[27]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.

al. (2011) note that antipsychotics are believed to substitute for nurse care and show that when nursing homes increase wages, inappropriate use of antipsychotics decreases. Therefore, 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 more use of antipsychotics and lower mobility. The two channels additively predict an increase in mortality of 0.5 pp in our setting (about 25% of our mortality effect). However, this may be an underestimate if they produce larger effects when they interact.

The increase in RN availability is consistent with the negative effects on mortality being driven by less complex patients. RN staff are most relevant for the more medicalized aspects of care, while front line nurses support daily living activities such as preventing infections and turning patients in bed. One possibility is that 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 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.[28] Given the tight regulatory scrutiny of RN availability, it is difficult to reduce staffing levels in this category.

To explore whether the declines in staff availability and quality are related, we compare changes in staff availability and Five Star ratings within target facilities around the PE buyout event. This analysis recovers correlations and does not imply causality, so we present the raw data in bin-scatter plots. Figure B.7 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.

[28] 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.

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%.[29] 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 associates with profits for PE owners. The first is what are often termed "monitoring fees" charged to portfolio companies. In the CMS cost reports, these are listed as "management fees"—charges to the nursing home for being owned and managed by a PE firm.[30] 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 6 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.

The second type of expenditure is lease payments. The value of underlying real estate is frequently cited as a reason that nursing homes and other typically low-margin assets can be profitable investments, because 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 particularly beneficial to the fund's Internal Rate of Return, a key 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:

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

[30] 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.

> "[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).[31]

Consistent with this strategy, column 2 shows that facility building lease payments increase dramatically by about 76% after PE acquisitions (we exponentiate large coefficients since the outcome is in log dollars). Figure 6 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 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 6 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 B.9 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 corresponding event study is presented in Figure B.8B and 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

[31] 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).

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 B.9 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 B.8C). Hence, the data are more consistent with the facility-level admissions increase reflecting business stealing.

7 Conclusion

This paper studies PE buyouts in healthcare, an important sector where PE activity has increased dramatically, generating policy debate. Nursing homes are a useful setting because they have particularly high levels of for-profit ownership and subsidy and have experienced extensive PE investments. In an instrumental variables design incorporating facility fixed effects, we address both targeting and patient selection challenges to identification. We find that going to a PE-owned facility increases 90-day mortality by about 14% for short-stay Medicare patients, while taxpayer spending over the 90 days increases by 11%. Consistent with unobserved risk-based selection, OLS estimates of mortality and spending are much lower. 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 work. Although our results imply PE ownership reduces productivity of nursing homes, it may have more positive effects in other sectors of healthcare with better functioning markets. Beyond healthcare, there has been significant PE investment in sectors such as education, defense and infrastructure, which like healthcare rely on high levels of government subsidy but are characterized by opaque product quality. Further work is needed to determine how government programs can be redesigned to align the interests of PE-owned firms with those of taxpayers and consumers.

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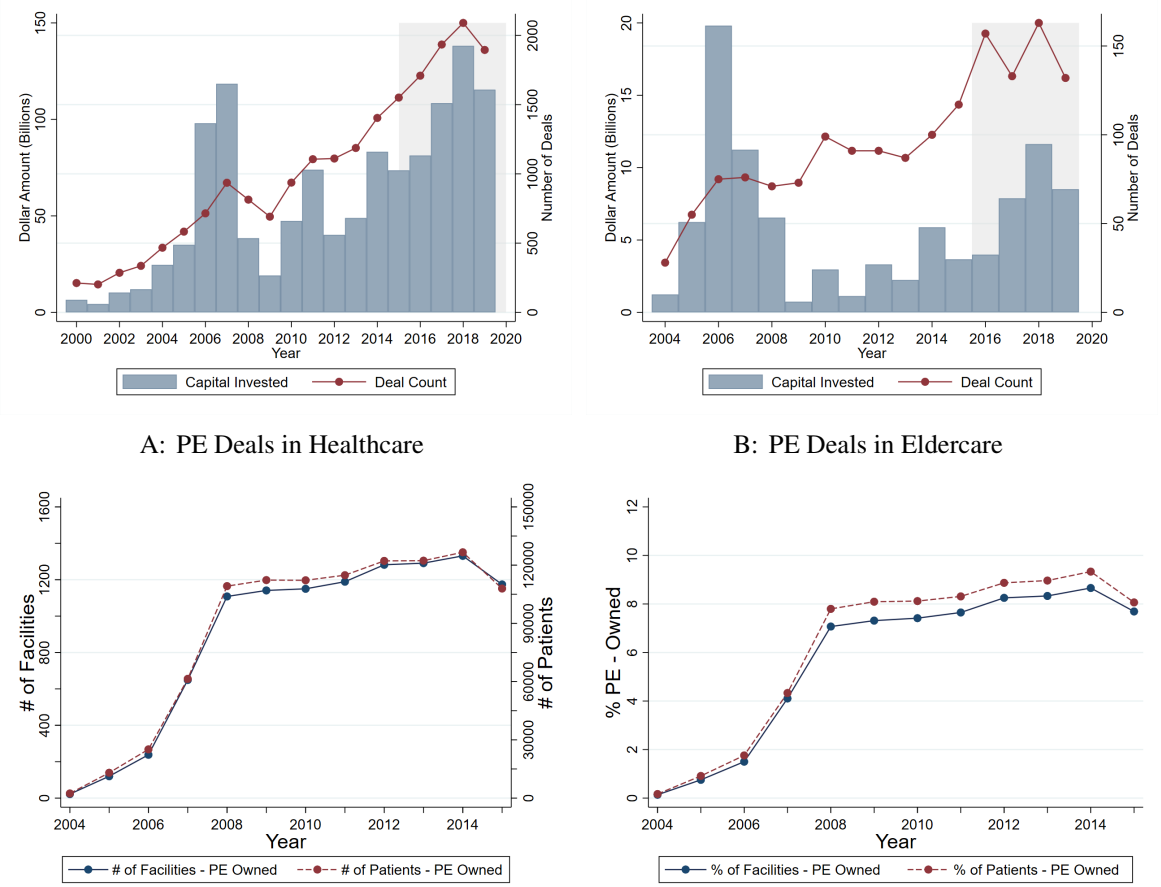
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Figures and Tables

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



A: PE Deals in Healthcare

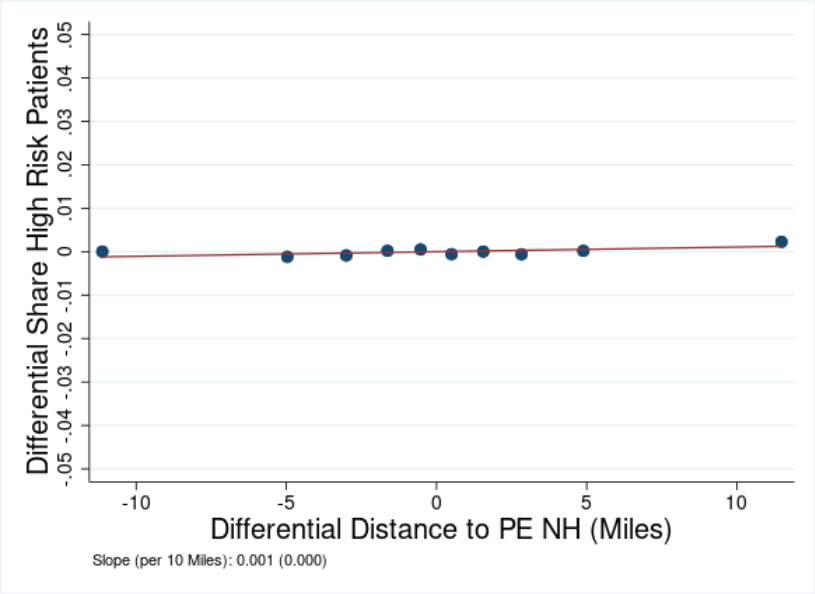
B: PE Deals in Eldercare

C: Number of Facilities and Patients Acquired

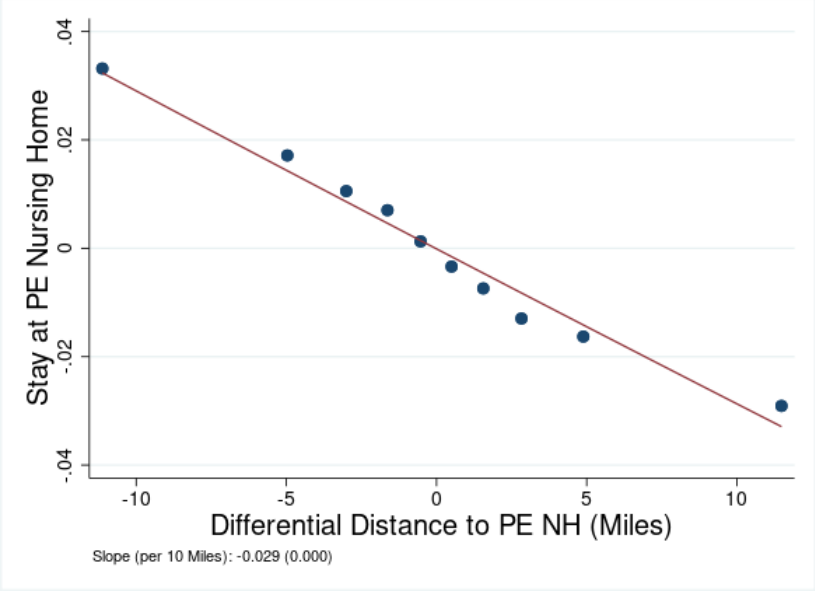
D: Percentage of Facilities and Patients Acquired

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: **Patient Characteristics with Differential Distance**



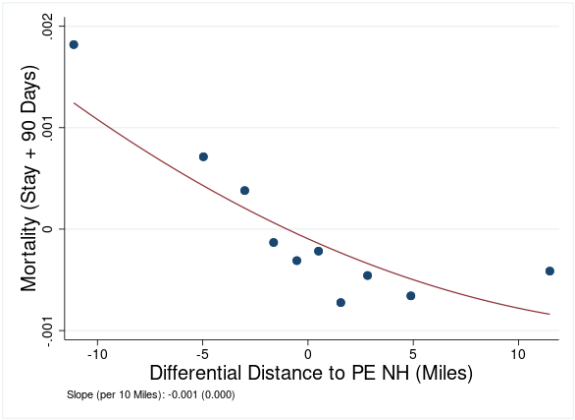
A: High Risk Patients



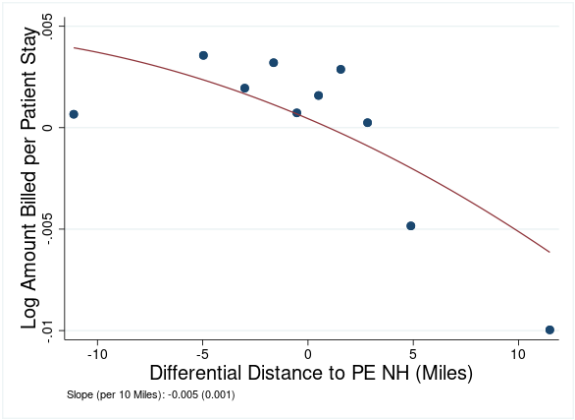
B: Stay at PE Nursing Home

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.

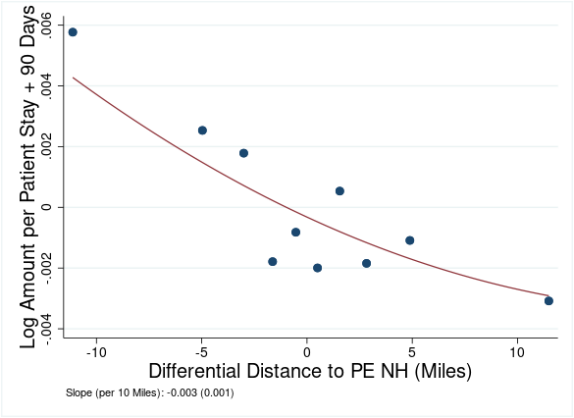
Figure 3: **Patient Outcomes with Differential Distance**



A: Mortality (Stay + 90 Days)



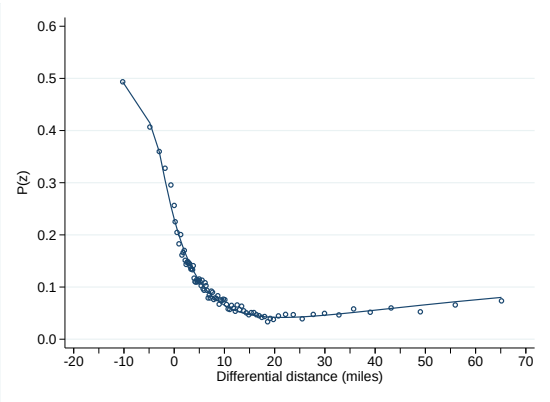
B: Log Amount Billed per Patient Stay



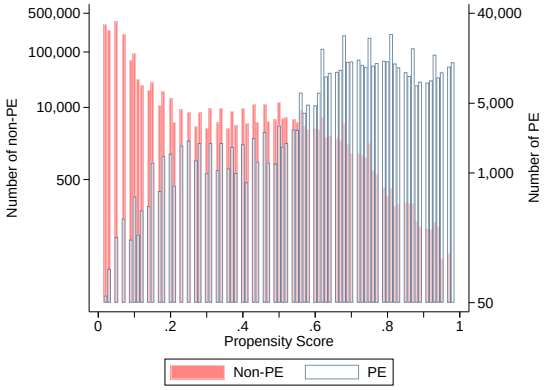
C: Log Amount Billed per Patient Stay + 90 Days

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 nurshing 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.

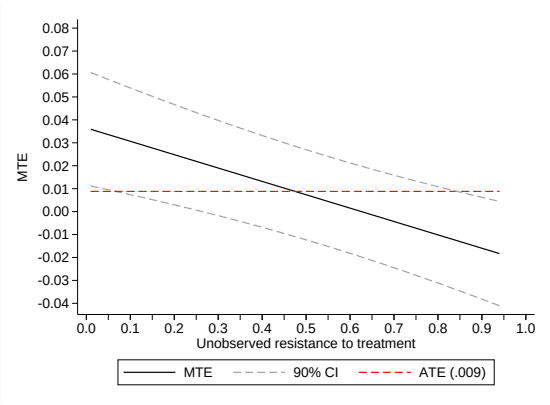
Figure 4: **Marginal Treatment Effects**



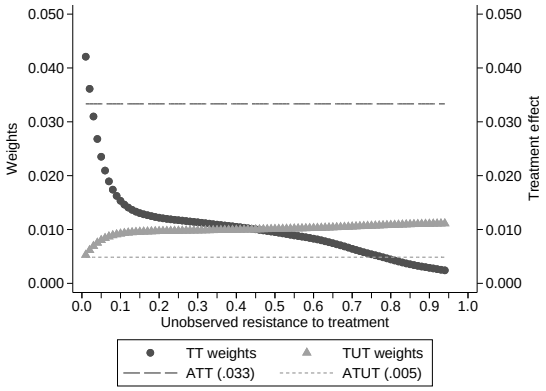
A: First stage



B: Common Support



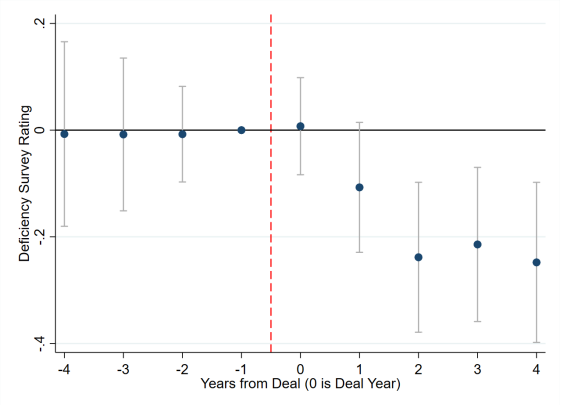
C: MTE curve



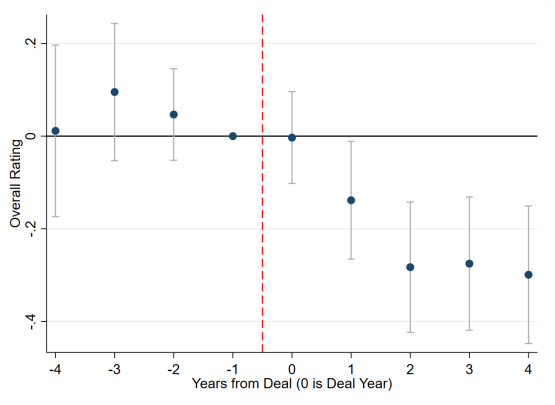
D: ATT and ATUT

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. Appendix figure B.6A presents the corresponding plot using a linear scale. 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 5.2.2 presents details of the MTE estimation.

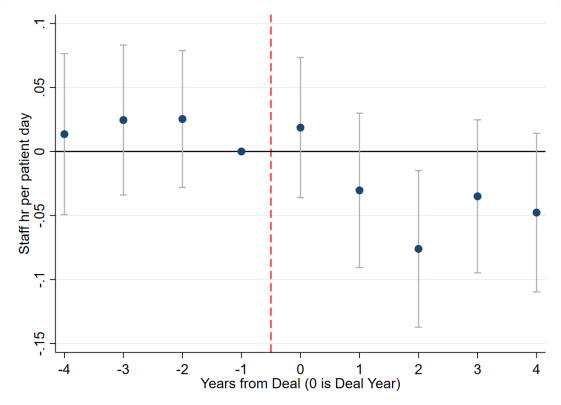
Figure 5: **Aggregate Quality and Staffing Outcomes**



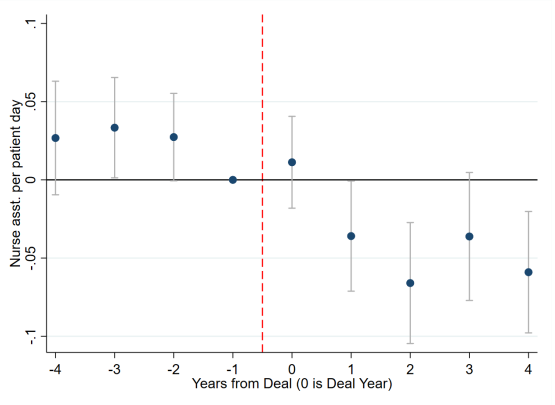
A: Deficiency Survey Rating



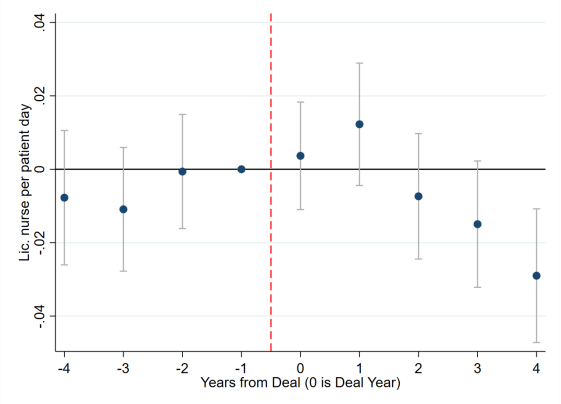
B: Overall Rating



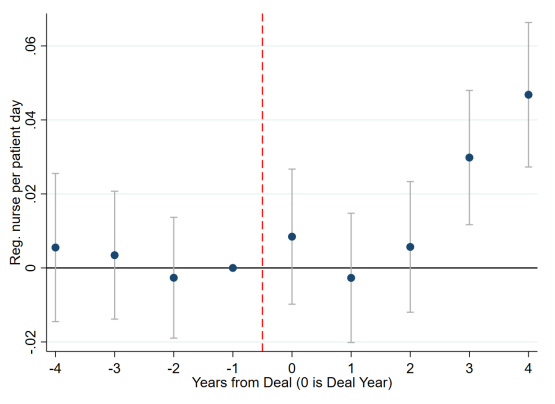
C: Staff Hour per Patient Day



D: Nurse Asst. per Patient Day



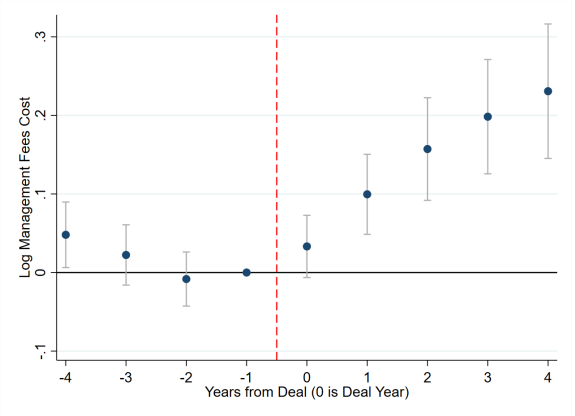
E: Lic. Nurse per Patient Day



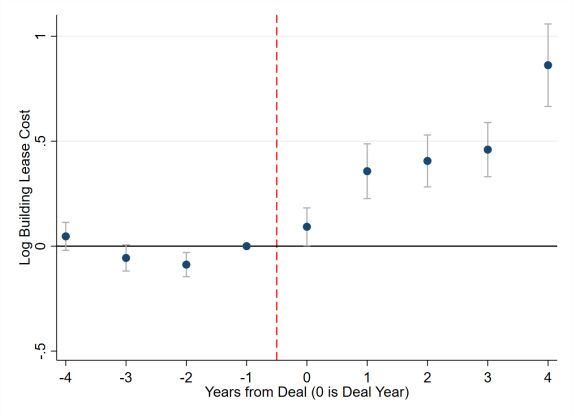
F: Registered Nurse per Patient Day

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 (10) 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.

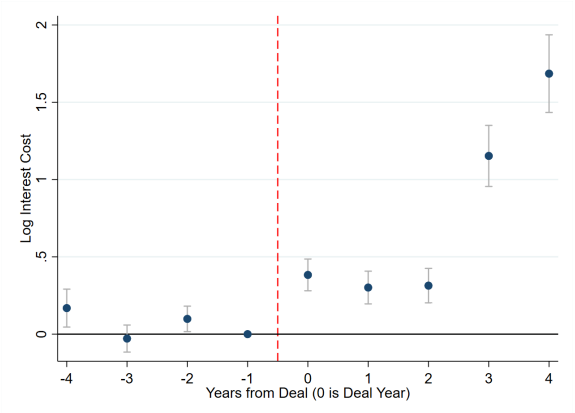
Figure 6: **Facility Finances**



A: Log Management Fee Cost



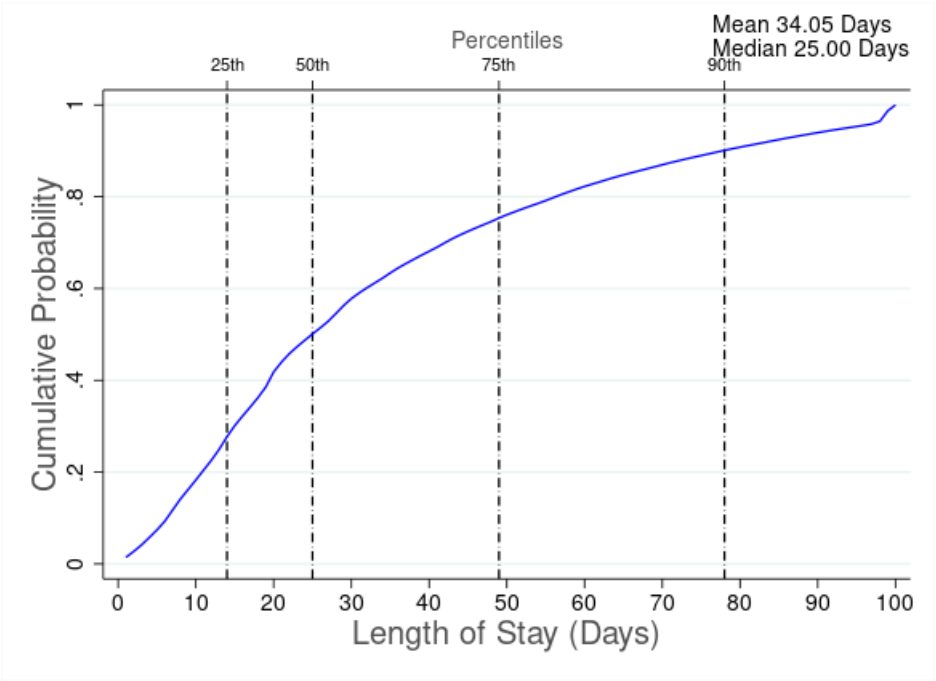
B: Log Building Lease Cost



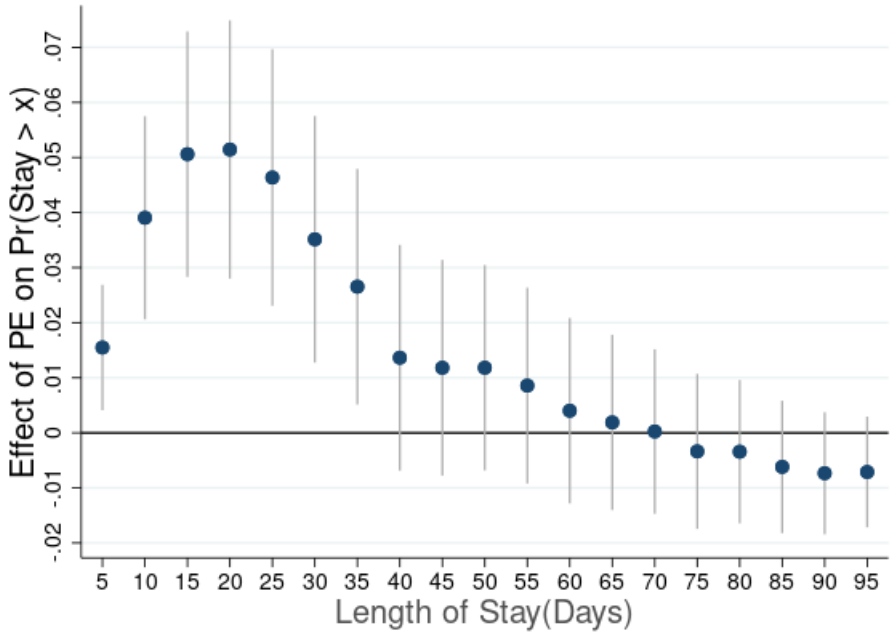
C: Log Interest Cost

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 (10) 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.

Figure 7: **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.

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, antipsychotics, mobility, and pressure ulcers. 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: **Patient-Level Analysis: First Stage**

	(1) 1(PE)	(2) 1(PE)	(3) 1(PE)	(4) 1(PE)
Differential Distance (In 10 Miles)	-0.0580*** (0.003)	-0.0580*** (0.003)	-0.0578*** (0.003)	-0.0381*** (0.002)
(Differential Distance)2 (In 10 Miles)	0.0077*** (0.001)	0.0077*** (0.001)	0.0076*** (0.001)	0.0057*** (0.000)
Market Controls			Y	
Patient Controls		Y	Y	Y
Facility FEs	Y	Y	Y	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 (1). 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 col. 2 but defines patient market using a narrower market definition: Hospital Service Area (HSA) instead of HRR. Standard errors are clustered by facility.

Table 3: **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 4: **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: 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	
	C: 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	
	D: 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	

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 - activities of daily living (ADL) score for patients where a higher score indicates more dependence, indicator for alzheimers, dementia, and depression. In Panel B, each cell presents the coefficient β obtained by estimating Equation (2) 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 claims-based patient quality outcomes - patient death within 90 days of discharge from the index stay, and total amount billed (2016$). Panel C presents these results from a placebo analysis of the relationship between private equity ownership and patient health and spending. For this analysis, we use data over 2002–07, a period with very little actual PE ownership and which has little overlap with the main analysis sample. 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. Accordingly we re-compute differential distance values taking into account these placebo acquisitions. Panel D presents OLS version of the same results. 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 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 4. 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, 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 panel The fifth 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 (2) 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: IV Estimates			
	(1) 1(Uses Anti-Psychotics)	(2) 1(Mobility Decreases)	(3) 1(Develops Ulcers)	(4) 1(Pain Intensity Increases)
1(PE)	0.0309***	0.0188*	-0.001	0.0338**
	(0.007)	(0.010)	(0.008)	(0.016)
Observations	5,305,056	5,305,056	5,305,056	5,305,056
Y-Mean	0.09	0.52	0.08	0.26
	B: OLS Estimates			
	(1) 1(Uses Anti-Psychotics)	(2) 1(Mobility Decreases)	(3) 1(Develops Ulcers)	(4) 1(Pain Intensity Increases)
1(PE)	0.0095***	0.0324***	0.0078**	0.0235***
	(0.001)	(0.003)	(0.003)	(0.005)
Observations	5,305,056	5,305,056	5,305,056	5,305,056
Y-Mean	0.09	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 coefficient β obtained by estimating Equation (2), and each cell in Panel B presents OLS version od the same results. 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. 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. The independent variable is an indicator for whether a nursing home is private equity-owned (=1 if PE-owned, 0 otherwise) starting in the next year from the deal announcement date. We present results for patient level outcomes - an indicator for patient using anti- psychotics, decrease in patient mobility, developing/worsening pressure ulcers, and increase in pain intensity. These variables take value one if this condition is not flagged for the patient in the initial assessment, but is flagged at some point during the stay. Standard errors are clustered by facility.

Table 8: **Mechanisms and Operational Changes**

	A: Five Star Rating			
	(1) Deficiency Rating	(2) Overall Rating		
1(PE) (No Control)	-0.075**	-0.079**		
	(0.037)	(0.036)		
1(PE) (With Control)	-0.077**	-0.082**		
	(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) (No Control)	-0.050***	-0.068***	-0.019***	0.037***
	(0.017)	(0.010)	(0.006)	(0.005)
1(PE) (With Control)	-0.048***	-0.066***	-0.019***	0.037***
	(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) (No Control)	0.074**	0.564***	1.181***	
	(0.032)	(0.061)	(0.096)	
1(PE) (With Control)	0.074**	0.560***	1.175***	
	(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 9 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, interest expenses, and cash on hand. 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.[32] 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 29,000 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.[33] 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 2004 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).[34] We use these files to track beneficiaries' demographics, spending, and health

[32] 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.

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

[34] 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.

outcomes such as mortality. The MDS helps observe clinical assessments such as mobility and the use of antipsychotic drugs.

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 seven 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, Feng, Hirth, Rahman and Mor, 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. 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.[35] 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, Szatrowski, Peterson and Gold, 1994).[36] 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 four measures of patient well-being which comprise inputs to the

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

[36] 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 starting antipsychotic medication during the stay. The second is an indicator for the patient's self-reported mobility score declining during the stay. The third is an indicator for developing a pressure ulcer. The fourth 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.[37] 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.[38]

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 B.1 shows the number of deals in each year. In total, our data contain 136 unique PE firms that acquired nursing homes. Most deals are syndicated and involve multiple PE firms. Table B.1 presents the top 10 deals by number of facilities acquired. Deal sizes are skewed, with the top 10 deals accounting for about 80% of all facilities acquired. On average, we observe PE-owned facilities for eight years post-acquisition.[39]

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 B.2. 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

[37] 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.

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

[39] A likely source of measurement error is not capturing PE disinvestment from facility ownership. For the top 10 deals (80% of facilities) 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.

of patients eligible for Medicare Advantage.

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 (11):

$$PE_{j,t} = \alpha_s + \alpha_t + X'_{j,t}\beta + \epsilon_{j,t} \tag{11}$$

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.[40] 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.

[40] 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.

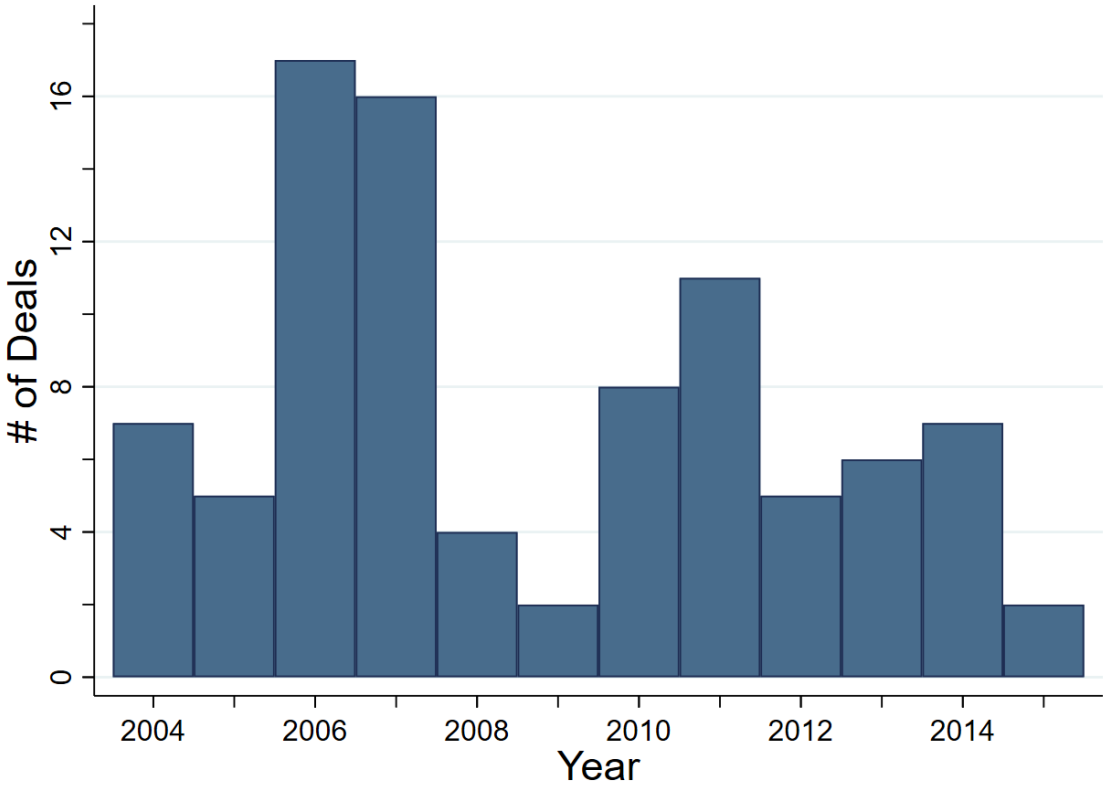
Table A.1: **Targeting**

	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.

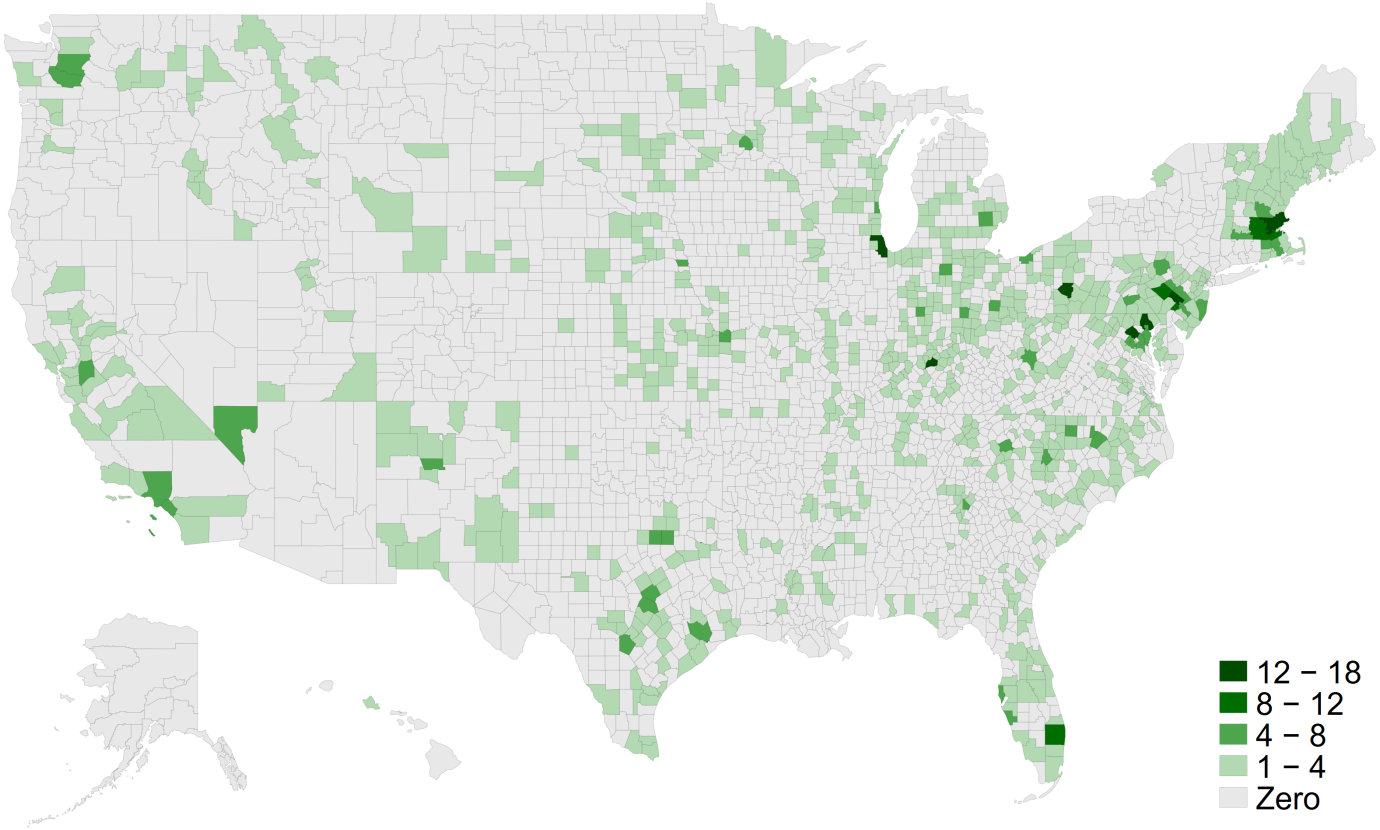
B Supplementary Figures and Tables

Figure B.1: **PE deals for Nursing Homes by Year**



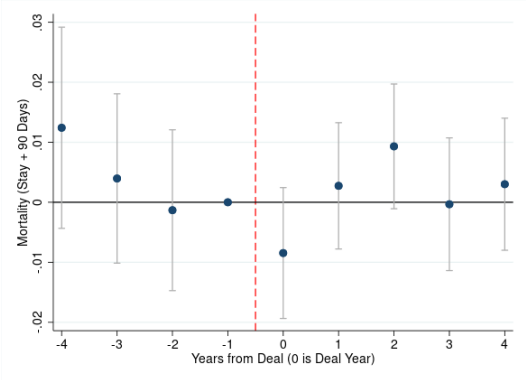
Note: This figure presents the number of unique deals for active nursing homes by PE firms for each year over the period 2004–2015.

Figure B.2: **Location of Private Equity Targets**

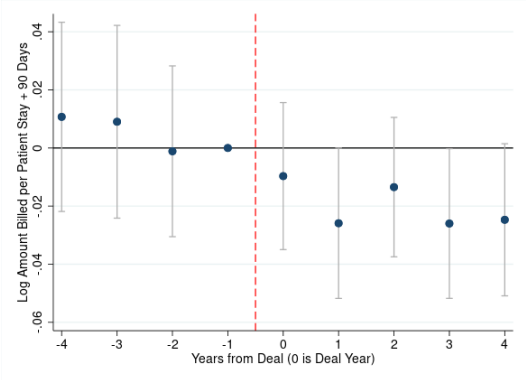


Note: This figure presents the number of facilities bought by PE firms in each county over the period 2004–2015. We identified 1,674 such facilities.

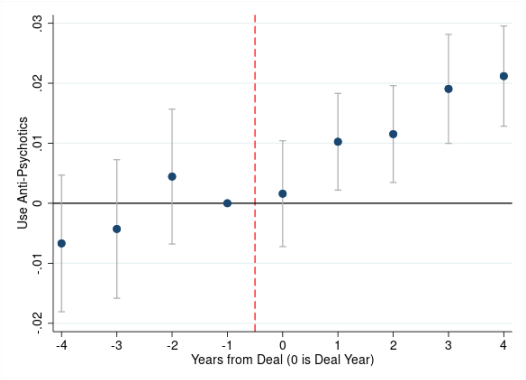
Figure B.3: **Patient Outcome Measures**



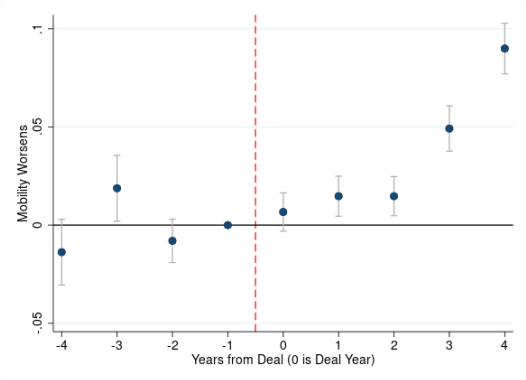
A: Mortality (Stay + 90 Days)



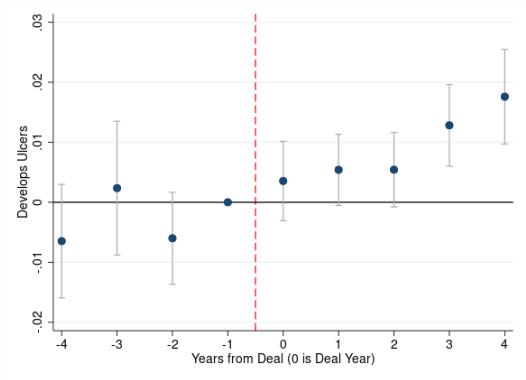
B: Log Amount Billed (Patient Stay + 90 Days)



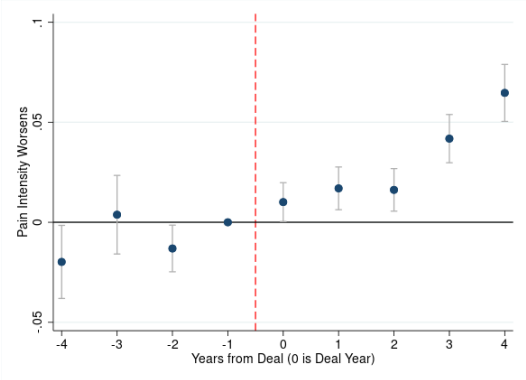
C: 1(Uses Antipsychotic Medications)



D: 1(Mobility Decreases)



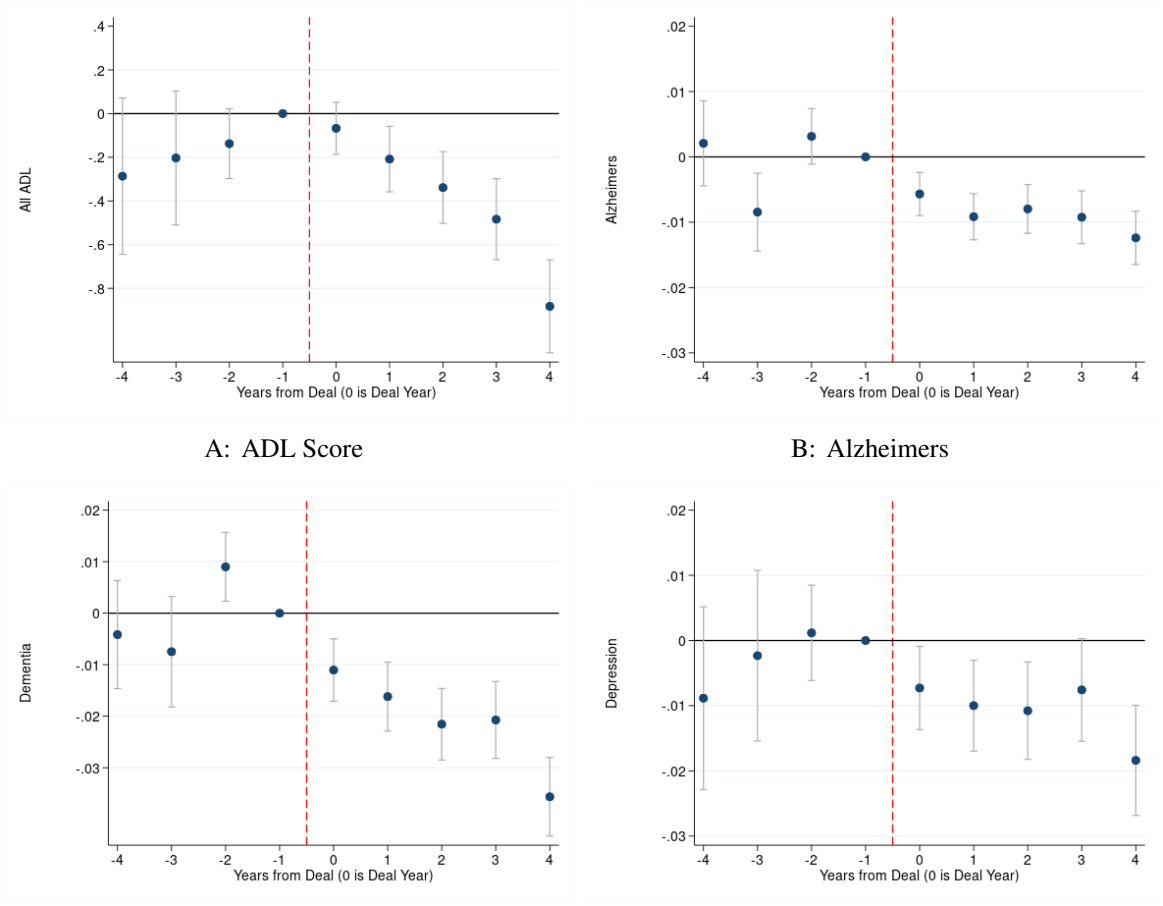
E: 1(Develops Ulcers)



F: 1(Pain Intensity Increases)

Note: This figure presents event studies on patient outcome measures around the time a nursing home experiences a PE buyout. To match the event study plots presented in the main text, we estimate these models on collapsed facility-year level data and use the same specification, i.e., facility and year fixed effects, patient mix, and market controls, as described in Section 6.1. Each point in the figures represents the coefficient β_s obtained by estimating Equation (10) as discussed in Section 6. 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 F present results for MDS assessment based outcomes - the facility level mean for indicators for patient using antipyschotics, 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 B.4: **Initial Patient Assessments**



A: ADL Score

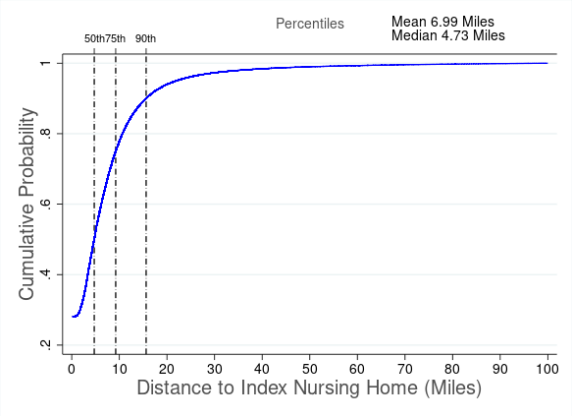
B: Alzheimers

C: Dementia

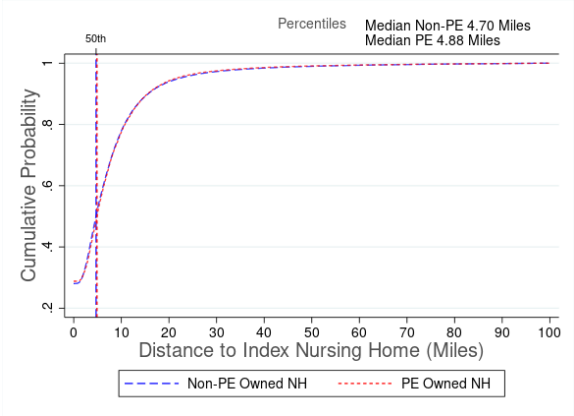
D: Depression

Note: This figure presents event studies on initial patient assessments around the time a nursing home experiences a PE buyout. To match the event study plots presented in the main text, we estimate these models on collapsed facility-year level data and use the same specification, i.e., facility and year fixed effects, patient mix, and market controls, as described in Section 6.1. Each point in the figures represents the coefficient β_s obtained by estimating Equation (10) as discussed in Section 6. 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.

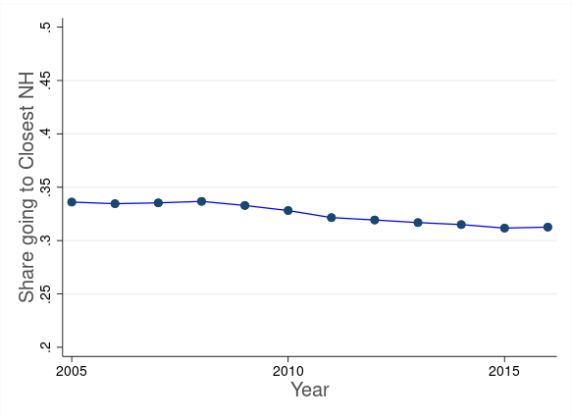
Figure B.5: **Patient distance to Nursing Home**



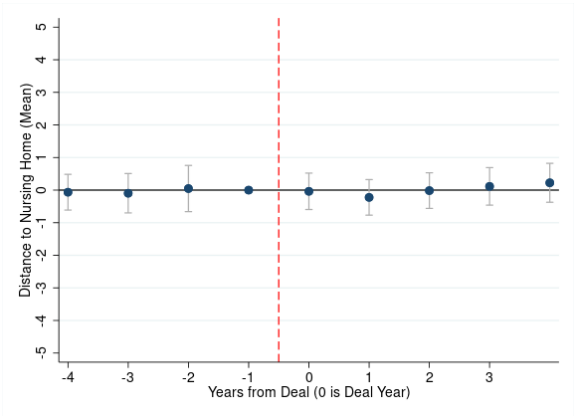
A: CDF: All Patients



B: CDF: PE vs. Non-PE Patients



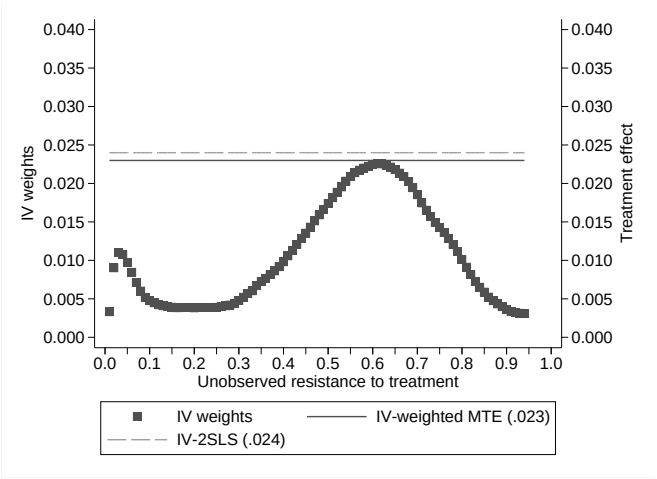
C: Trendline: Share going to Closest Nursing Home



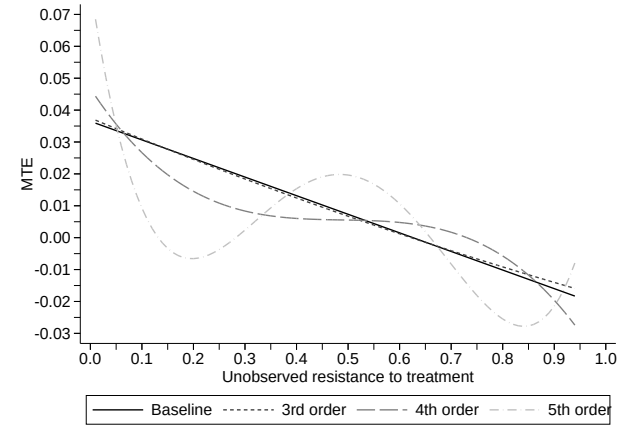
D: Event Study: PE Acquisition

Note: This figure provides descriptes 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 (10) 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 B.6: **MTE specification checks**



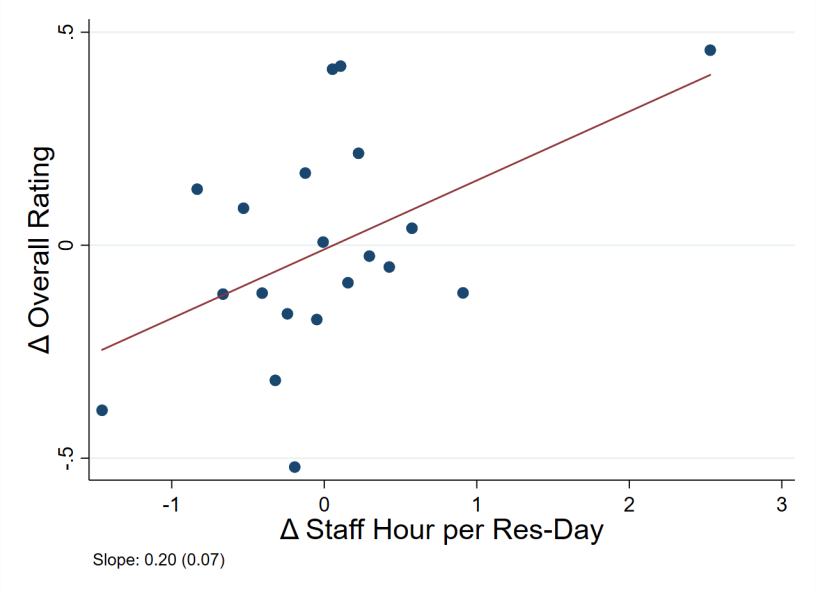
A: IV estimate



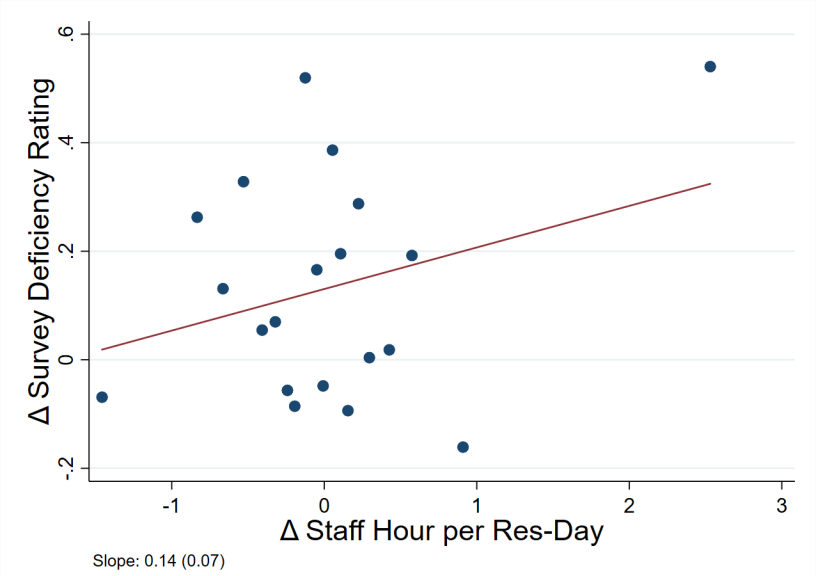
B: Order of polynomial

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 5.2.2 presents details of the MTE estimation.

Figure B.7: **Staff Availability and Five Star Ratings**



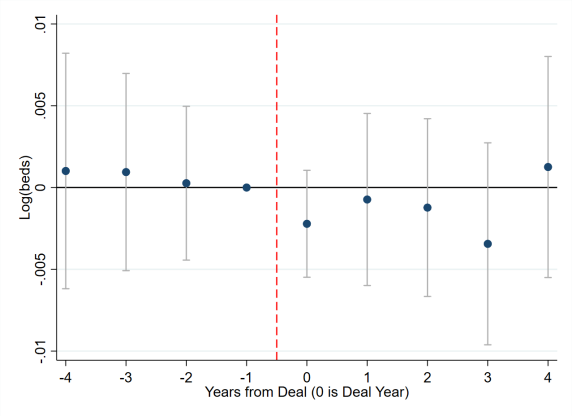
A: Overall Rating



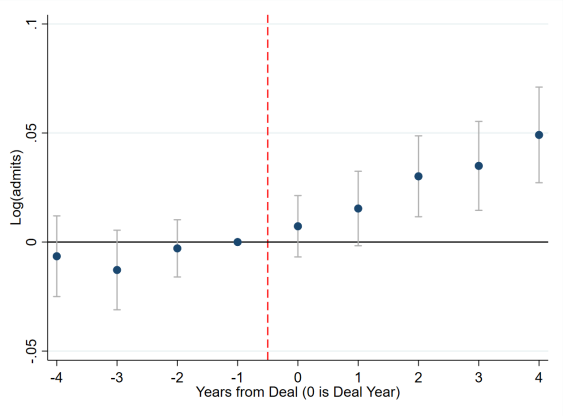
B: Deficiency Rating

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.

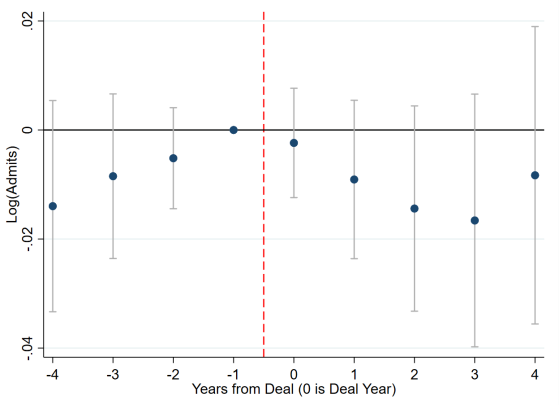
Figure B.8: **Patient Volume**



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 (10) 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 B.1: **Top 10 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
6	Skilled Healthcare Group	Onex, Heritage Partners	2005–07	76
7	Trilogy Investors	Lydian Capital Partners	2007–15	65
8	Lavie Care Centers	Formation Capital, Senior Care Development	2011	61
9	Laurel Health Care Company	Formation Capital, Longwing Real Estate Ventures	2006–16	41
10	Harden Healthcare	NXT Capital, Oaktree Speciality Lending	2013	35

Note: This table presents some details on the top 10 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 B.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. Details are available in Section 4.2. 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 B.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 (2) 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 4. 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 B.4: **Effects for different groups based on 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 $\times$ year fixed effects. Standard errors are clustered by facility.

Table B.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	223.8	223.8	223.8	223.8	223.8
Coefficient/ Y-Mean	14%	13%	15%	14%	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 (2) 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 B.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 Dartmouth 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 (2) 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 B.7: **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 Table 8. Each cell presents the coefficient β obtained by estimating Equation (9) 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 B.8: **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 9). 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 (9) 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 B.9: **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 (9) 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.