Healthcare Provider Bankruptcies*

Samuel Antill
Harvard University

Jessica Bai
Harvard University

Ashvin Gandhi
UCLA & NBER

Adrienne Sabety
Stanford University & NBER

March 20, 2025

Abstract

Healthcare firms are filing for Chapter 11 bankruptcy at record rates. We find that bankruptcies increase healthcare staff turnover, worsen care, and harm patients. Using a difference-in-differences design, we estimate that a bankruptcy filing immediately increases staff turnover and worsens the firm's performance on unannounced inspections. Next, using a patient-distance-to-facility instrument, we document that bankruptcies harm patients through increases in hospitalizations, physical restraints, and bedsores. Finally, we employ a randomized survey experiment of nursing home staff to confirm that bankruptcy filings increase voluntary departures and that replacement workers harm patients.

*We thank Tomoro Harris, Yoon Sang Moon, Daniel Neagu, Sangwook Suh, Fuman Xie, and Yan Bo Zeng for their excellent research assistance. We thank Leemore Dafny, David Chan, Riley League, Tong Liu, Atul Gupta, Jon Kolstad, Maria Polyakova, Brian McGarry, Song Ma, Andrew Olenski, Maya Rossin-Slater, David Slutsky, Mark Shepard, and Maggie Shi for useful feedback. We appreciate helpful comments from conference participants at NBER Summer Institute, Utah Winter Economics Conference, Stanford Economics Junior Faculty Seminar, the Wharton Restructuring Conference, the Annual Health Economics Conference, Bates White Life Sciences, the Occasional Berkeley Health Economics Conference, Whistler Junior Health Economics Summit, American Society of Health Economics Conference, UBC Winter Finance Conference, as well as seminar participants at the Harvard Graduate Student Finance Workshop, Harvard-MIT-BU Health Economics Seminar, the University of Kansas, Ohio State University, and UCSD Applied Economics Seminar. Our experimental design and analysis plan were preregistered with the American Economic Association RCT Registry (#10335) on November 2, 2022. This study has been approved by Harvard's Institutional Review Board (Protocol IRB22-1066), UCLA's Institutional Review Board (Protocol IRB22-001483), and Stanford's Institutional Review Board (Protocol 67509 deemed not human research).

1 Introduction

Total debt in the United States healthcare sector has doubled since 2019. A rise in debt-financed acquisitions and declining profits have prompted an uptick in healthcare provider bankruptcies (Balasubramanian, 2023). As a result, Moody's now rates 80% of North American healthcare companies' debts as speculative grade, indicating substantial default risk (Landi, 2022). In theory, a Chapter 11 bankruptcy could resolve a healthcare firm's default through reorganization with little impact on the firm's operations. However, there is virtually no empirical evidence on how Chapter 11 bankruptcy impacts healthcare firms. Chapter 11 is designed to maximize value for financial stakeholders, but how does a reorganization affect healthcare workers and patients?

Using rich administrative data on healthcare provider employment and patient outcomes, we show that Chapter 11 bankruptcy filings negatively affect healthcare firms and their patients. The high-frequency nature of our data isolates the impact of a bankruptcy filing from declining firm performance. Employing a matched difference-in-differences (DiD) event study design, we document an immediate increase in worker turnover and health-inspection violations after a bankruptcy filing. We then study patient outcomes using an instrumental-variable (IV) approach to account for the endogenous sorting of patients into bankrupt versus nonbankrupt healthcare facilities. We find that residents of bankrupt facilities are more likely to be readmitted to the hospital, indicating a substantial decline in a resident's health. Finally, to confirm that voluntary worker turnover causes worse patient outcomes, we survey experienced healthcare workers through a randomized survey experiment. We show that, according to workers, (i) a bankruptcy filing causes an increase in voluntary departures and (ii) hiring new workers to replace departing workers worsens the quality of patient care.

Our analysis focuses on the healthcare industry; U.S. healthcare spending exceeds the GDP of most countries, at 17.6% or $4.9 trillion dollars per year (Centers for Medicare & Medicaid Services, 2025; World Bank, 2025). It is also a sector where patients' lives are at stake. Within the healthcare industry, we focus on nursing homes, which house 1.3 million patients receiving skilled medical care. Nursing homes are an ideal setting for two reasons. First, the nursing home industry is broadly representative of the healthcare sector. Nursing homes have experienced high bankruptcy rates like other healthcare firms, possibly due to debt-financed acquisitions (Gandhi, Song, and Upadrashta, 2022; Gupta et al., 2024) or financial engineering (Gandhi and Olenski, 2024). Second, rich regulatory datasets specific to the nursing home industry allow us to observe the sector comprehensively. We observe every worker for every nursing home in the United States. Similarly, we observe virtually

every nursing home patient.

To construct our comprehensive sample, we start from the universe of corporate bankruptcy filings and identify every Chapter 11 bankruptcy filed by a nursing home from January 2010 to March 2020. Through a Freedom of Information Act (FOIA) request, we create a novel mapping between bankruptcies and detailed healthcare provider records collected by the Centers for Medicare and Medicaid Services (CMS). We observe worker departures and hour reductions, along with a description of the worker's role, for every worker at a daily frequency. We also obtain patient health data through health inspections, patient claims, and patient health assessments for every patient residing at a nursing home in the United States.

We use a DiD design to estimate the causal effects of a bankruptcy filing on worker outcomes and healthcare-facility inspections. Our identifying assumption is that the treatment group (bankrupt facilities) would have been on a parallel trend to the control group (nonbankrupt facilities) in the absence of treatment. A potential concern with this assumption is that negative unobservable shocks could cause both bankruptcy filings and changes in facility outcomes. We address this concern in two ways. First, we exploit the high-frequency data to isolate changes in a tight window around each bankruptcy filing. We estimate treatment effects within weeks or months of a bankruptcy filing, rather than years. Therefore, any confounding unobservable negative shocks to our treatment group would have to occur almost precisely at the bankruptcy-filing times. Second, we use a stacked-cohort-DiD design to compare each treated facility to a cohort of observably similar matched control facilities: before each treated firm's bankruptcy, it is similar to its matched controls along several dimensions (size, patient composition, and occupancy rates). We show that our results also hold using a staggered DiD design which only includes facilities that file for bankruptcy during our sample period. Importantly, our experimental results described below confirm our DiD results, further validating our parallel-trends assumption: any alternative explanation for our DiD results would have to also explain our experimental results.

We first document that worker departures spike immediately after a facility files for bankruptcy, relative to comparable nonbankrupt facilities. In the year after a bankruptcy filing, weekly worker departures increase by 10% of the mean. New workers are hired to replace exiting workers almost one for one: weekly worker hires increase by 8% of the mean. This result implies that bankrupt firms maintain staffing levels to promote a successful reorganization. However, this turnover leads to a dramatic shift toward inexperienced workers after a bankruptcy filing.

Do workers depart voluntarily in response to a bankruptcy filing, or are they fired by

the bankrupt firm? We document three pieces of empirical evidence that strongly suggest worker departures are voluntary (rather than layoffs). First, in a survey experiment that we describe below, experienced healthcare workers report that bankruptcies increase voluntary worker departures. Second, we show that wages rise after a bankruptcy, which is consistent with voluntary turnover: workers are less interested in working for the bankrupt facility, so the facility must increase pay to attract and retain staff. Specifically, we obtain data on healthcare provider cost reporting and find that the wages of the highest certification nursing staff increase following bankruptcy. Third, we document a shift in staffing away from wage workers and toward more costly contract staff. This is another way that bankrupt firms increase staff pay, which is consistent with voluntary turnover by the above logic.

Next, we turn to administrative data on facility health inspections. Using a similar DiD design, we show that health inspections are more likely to indicate low-quality patient care after a facility files for bankruptcy.

The above result suggests that patients are harmed by nursing home bankruptcies. We directly test this using patient-level CMS data on health outcomes. We show that a bankruptcy filing leads to worse outcomes for the bankrupt facility's patients, relative to the counterfactual outcomes that those patients would have experienced at a nonbankrupt facility. To measure this counterfactual, we overcome two endogeneity concerns. First, bankrupt facilities are different from nonbankrupt facilities. By including facility fixed effects, we control for any time-invariant unobservable facility characteristics. Second, patients of bankrupt facilities might differ from patients of nonbankrupt facilities on important dimensions. We account for this with an IV approach. Our instrument exploits the well-known fact that patients prefer nursing homes located close to their homes (Gupta et al., 2024). Formally, we estimate a distance-based discrete-choice model (Einav, Finkelstein, and Mahoney, 2024). The model reveals the probability that a given patient will choose a given facility *based purely on location preferences*. Our instrument is the probability that a patient will choose a bankrupt facility given (i) the distances between the patient and nearby facilities and (ii) the model-implied preference for proximate facilities.

Intuitively, our IV approach defines a patient to be treated by a facility's bankruptcy if she is *close* to the bankrupt facility, regardless of whether she *selects* the bankrupt facility. We find that patients who are physically close to a bankrupt facility are more likely to receive care at a bankrupt facility. Using ZIP-code clustered standard errors, we find that the F statistic for the instrument is 1,736. Moreover, several tests suggest that the instrument is uncorrelated with various patient characteristics once we condition on control variables.

This result validates the exclusion restriction.

Using this instrument, we show that nursing home bankruptcies cause an increase in patient hospitalization rates. Formally, bankruptcies increase the share of nursing home patients who are hospitalized within 90 days of nursing home admission. The probability of hospitalization increases by 1.44 percentage points (4.1% of the average hospitalization rate). This is alarming because hospitalization is a very poor outcome for a nursing home patient. Hospital patients are admitted to a nursing home facility when their health improves, so returning to the hospital after a facility stay indicates a substantial decline in health. We find that hospitalization is more likely if a patient visits a bankrupt facility, relative to the counterfactual of the same patient visiting the same facility before its bankruptcy.

We find that bankruptcies harm patients along other meaningful dimensions. Bankruptcies increase the use of physical restraints by 1.5 percentages points, which is 77% of the sample mean. Patients at a bankrupt facility are thus more likely to be *restrained against their will* (e.g., tied to a bed). CMS strongly discourages this type of physical-restraint use. Similarly, bankruptcies increase the rate of patients developing bedsores by two percentage points (14% of the sample mean). Both of these results suggest that staff at bankrupt facilities mistreat patients by taking harmful shortcuts (e.g., infrequently repositioning patients). We find that these results are robust to using a simpler "differential-distance" instrument as in Gupta et al. (2024). Indeed, when we use the differential-distance instrument, we find a stronger impact of bankruptcy on hospitalization rates and patient mistreatment. Importantly, these health impacts of bankruptcy are distinct from the impacts of private-equity ownership documented by Gupta et al. (2024) and Gandhi, Song, and Upadrashta (2022): Among all the bankrupt facilities in our sample, fewer than 5% were involved in a private-equity buyout in the 10 years leading up to the bankruptcy.

Is this increase in hospitalization rates and patient mistreatment caused by staff turnover or some other feature of bankruptcy? To validate the causal link between turnover and patient outcomes, we design and conduct an online experiment to elicit the beliefs of 247 nurses with nursing home work experience. The participant responses indicate that the bankruptcy-induced staff turnover we document is harmful for patients. Moreover, the responses confirm that a facility bankruptcy filing causes voluntary worker departures.

Specifically, we first use the experiment to estimate how nursing home bankruptcies affect voluntary worker attrition. We describe a hypothetical nursing home. For participants randomly assigned to our treatment group, the nursing home is reorganizing in Chapter 11 bankruptcy. Each participant uses their work experience to estimate (i) the overall rate

of voluntary worker departures at this hypothetical facility and (ii) the probability that they would search for a new job if they were an employee of the nursing home. Holding everything else fixed, a bankruptcy filing causally increases estimated voluntary departures by 18 percentage points (47% of the control-group mean). When participants estimate their own probability of searching for a new job, bankruptcies causally increase the likelihood of searching by 30 percentage points.

Finally, the second part of our experiment shows that staff turnover harms patients. We describe a hypothetical nurse caring for a patient. In a randomly assigned treatment group, the nurse's tenure at the facility is reduced from one year to one week. Holding everything else fixed, this reduction in nurse tenure increases the participant-estimated likelihood of a negative patient outcome by 10 percentage points (44% of the mean). Our empirical results thus align with the beliefs of the experienced nursing home staff that we survey.

Contribution to the literature. We provide the first evidence on the impact of Chapter 11 bankruptcies on healthcare workers and patients. Our paper contributes to work studying how healthcare firms' financial decisions impact patients (Adelino, Lewellen, and Sundaram, 2015; Adelino, Lewellen, and McCartney, 2022; Aghamolla, Karaca-Mandic, Li, and Thakor, 2024; Liu, 2021; Gandhi, Song, and Upadrashta, 2020, 2022; Gupta, Howell, Yannelis, and Gupta, 2024; Griffin and Priest, 2025) and the impact of a firm's financial distress on the firm's workers (Baghai, Silva, Thell, and Vig, 2021; Falato and Liang, 2016; Brown and Matsa, 2016; Gortmaker, Jeffers, and Lee, 2022; Graham, Kim, Li, and Qiu, 2023; Araujo, Ferreira, Lagaras, Moraes, Ponticelli, and Tsoutsoura, 2023; Ellias, 2022; Berk, Stanton, and Zechner, 2010) and customers (Hortaçsu, Matvos, Shin, Syverson, and Venkataraman, 2011; Matsa, 2011; Hortaçsu, Matvos, Syverson, and Venkataraman, 2013; Phillips and Sertsios, 2013; Antill and Hunter, 2021). Differing from this literature, we contribute the first evidence that a healthcare firm's Chapter 11 bankruptcy filing harms both workers and patients. This contribution is distinct from earlier findings that private-equity ownership harms nursing home patients: among all the bankrupt facilities in our sample, fewer than 5% were involved in a private-equity buyout in the 10 years leading up to the bankruptcy.

This paper also contributes to work identifying determinants of healthcare provider quality and how disruptions to patients' care adversely affects health (Sabety, Jena, and Barnett, 2021; Schwab, 2023; Sabety, 2023; Agha et al., 2022; Agha, Frandsen, and Rebitzer, 2019). Most notably, Olenski (2023) finds that nursing home closures result in a 16% spike in mortality. We contribute to this literature by showing that bankruptcy filings, which are intended to relieve financial distress and avoid closure, cause worker turnover and negative

patient outcomes.

The remainder of the paper is organized as follows. Section 2 describes the setting. Section 4 describes the nursing home and bankruptcy data. Section 5 presents high-frequency employment responses to bankruptcy. Section 6 presents the analysis of the impact of bankruptcy on healthcare quality and patient outcomes. Section 7 contains the design and results of the randomized experiment. Section 8 concludes.

2 Empirical Setting

2.1 Nursing Home Industry

Nursing homes, known formally as skilled nursing facilities (SNFs), are certified by CMS to provide skilled nursing services, rehabilitative therapy, and other healthcare services requiring residence in an institutional setting. Facilities serve a wide range of patients, from short-stay patients receiving rehabilitative care after a hospitalization to long-stay patients receiving treatment for chronic conditions.

The U.S. nursing home industry is a nearly $200 billion industry. It consists of more than 15,000 facilities employing approximately 1.4 million staff serving more than 1.3 million residents each day. Nursing home quality has been a long-standing concern (U.S. Senate, 1960, 2024) for three reasons. First, nursing home care is primarily financed by the government through Medicare and Medicaid. Second, nursing home residents are a highly vulnerable population of older Americans, with nearly half suffering from dementia or cognitive impairment (Mukamel et al., 2023). Third, quality of care is atrocious: one in three Medicare patients experienced an adverse event that caused harm or death as a result of low-quality care received in a nursing home (of Inspector General, 2014). To address these concerns, regulators carefully monitor the quality of nursing home care. Regulators measure quality along dimensions detailed below.

Staffing. Nursing home care is extremely labor intensive, as it involves substantial care planning and frequent intimate interactions with patients to provide medical care and to assist with activities of daily living. Therefore, both regulators and researchers consider a facility's level of staffing (Clarke and Donaldson, 2008; Harrington et al., 2016; Lin, 2014; Centers for Medicare & Medicaid Services, 2019; Friedrich and Hackmann, 2021), as well as its retention of experienced staff who are familiar with the facility and its residents (Gandhi, Yu, and Grabowski, 2021; Loomer et al., 2021; Shen, McGarry, and Gandhi, 2023) to be

principal indicators of quality. Indeed, some states tie Medicaid payment rates to staffing levels and staff experience (Gandhi et al., 2024b), and CMS' Nursing Home Compare five-star rating system evaluates facilities on both staffing levels and staff retention (Centers for Medicare and Medicaid Services, 2025).

There are three primary nursing staff roles at skilled nursing facilities: registered nurses (RN), licensed practical nurses (LPN), and certified nursing assistants (CNA). RNs are highly skilled nursing staff who must obtain a two-to-four year degree or diploma in nursing and pass a licensing exam. LPNs are also required to have a degree or diploma in nursing and pass an exam, though these courses often take just one year to complete. CNAs need only complete a one-to-three-month training program. The Bureau of Labor Statistics lists the nationwide median hourly wages for RNs, LPNs, and CNAs in 2020 as $36.22, $23.47, and $14.82, respectively. Given the varying levels of training and certification across nursing roles, staffing quality measures and regulations typically differentiate between RN, LPN, and CNA hours. For example, CMS computes staffing star ratings based on both RN hours and total hours (i.e., RN+LPN+CNA hours). Likewise, the federal staffing minimums established by CMS in 2024 require a minimum number of RN hours and a minimum number of total hours.

The importance of staff tenure. Staff tenure is a key dimension of facility quality. High turnover—and correspondingly having a large share of new staff—has long been considered a concerning indicator of low-quality care (Carter and Phillips, 1988; Gandhi, Yu, and Grabowski, 2021). Nursing home staff must be trained in and implement processes that are specific to each facility and its residents. Correspondingly, it's unsurprising that facilities with high staff turnover perform worse on quality measures (Castle, Engberg, and Men, 2007), and those employing a large fraction of low-tenure staff are more likely to be cited for violating infection control protocols (Loomer et al., 2021). Moreover, nursing home residents have very individualized needs and are highly dependent on staff for activities of daily living—such as eating, bathing, dressing, toileting, and moving—so we might expect the common finding that consistent care teams yield better health outcomes (Wasson et al., 1984; Nyweide et al., 2013; Sabety, Jena, and Barnett, 2021) to apply particularly strongly in the nursing home industry. An instrumental variables analysis by Antwi and Bowblis (2018) indeed suggests a causal relation between nurse turnover and increased survey deficiencies.

Consistent assignment of nursing staff to residents has been increasingly emphasized as a policy goal (Roberts, Nolet, and Bowers, 2013). Turnover and tenure are such important measures of quality that the Affordable Care Act mandates that CMS collect and publicize

"information on employee turnover and tenure." Starting in January 2021, CMS began publishing turnover measures on Nursing Home Compare—a tool that many consumers use to compare and choose a nursing home. Starting in July 2021, turnover began to affect facilities' five-star rating—the most salient summary quality measure on Nursing Home Compare.

Health inspections. CMS requires state health departments to perform rigorous standardized inspections on each nursing home. Inspections are unannounced and must, on average, occur at least annually, with no more than 15 months between inspections (Centers for Medicare and Medicaid Services, 2023). The median inspection takes four days, and inspections frequently involve multiple inspectors. Inspectors can issue facilities citations for failing to meet any of approximately 200 standards affecting the health and safety of residents. The vast majority of facilities receive some citations each year, and CMS uses a composite score of citations as the primary measure of quality on Nursing Home Compare.

Resident assessments and health outcomes. In addition to staffing and health inspections, facilities are also frequently evaluated based on patients' health outcomes. These outcomes are measured using two sources of data. First, mandated regular assessments of nursing home patients detail the patients' care (e.g., are they being physically restrained or prescribed antipsychotics) and the patients' health (e.g., their cognitive function, whether they have bedsores or a UTI, and their performance of activities of daily living). Second, Medicare claims provide information such as whether a resident required rehospitalization after beginning nursing home care. CMS utilizes indicators of poor quality care—such as rehospitalizations and the use of physical restraints—when constructing quality ratings for nursing homes.

2.2 Bankruptcy

Firms use Chapter 11 bankruptcy to restructure debt, renegotiate contracts, or sell assets. Typically, a firm files for Chapter 11 because it cannot pay its debts.

Some firms use Chapter 11 to repay lenders by selling assets (11 U.S. Code §363). In an acquisition, the bankrupt firm sells its operations to another firm that continues to run the business. In a *liquidation*, the bankrupt firm sells all of its assets and shuts down.[1]

[1]Large firms typically liquidate in Chapter 11 rather than "Chapter 7," where liquidations are administered by bankruptcy lawyers with minimal business experience and fees are higher (Antill, 2024).

However, most bankrupt firms file for Chapter 11 to *reorganize*. In a successful reorganization, creditors exchange existing debt claims for equity claims on the firm's future profits. This exchange reduces the firm's debt to a sustainable level, allowing it to exit bankruptcy and continue operating. Importantly, the bankruptcy judge cannot confirm a reorganization if a liquidation would have produced more value for creditors (11 U.S. Code §1129(a)7). In this sense, a firm must be profitable to reorganize. For this and other reasons, not all reorganizations are successful: roughly 25% of large Chapter 11 cases conclude with a liquidation in which the firm shuts down (Antill, 2022).

During a reorganization, the firm's management continues to run the firm. For example, a reorganizing nursing facility continues to pay employees and provide patient care. The reorganization concludes once management, lawyers, creditors, and other stake holders reach a sufficient level of consensus supporting a reorganization plan (i.e., the equity claims or other payments that each party receives) and the judge confirms the plan. This complex negotiation process usually takes 1-2 years.

In theory, a reorganization could have no consequences for a firm's operations. For some firms, bankruptcy is a brief and purely financial transaction in which lenders exchange debt for equity: the technology firm Belk completed a reorganization in 12 hours (Borders and Blank, 2021). In practice, many firms use Chapter 11 to break lease contracts and significantly downsize their operations (11 U.S. Code §365). Moreover, the risk of a potential liquidation can cause some suppliers or employees to leave the firm.

Bankruptcy and employees. The bankruptcy code acknowledges that a firm cannot reorganize unless it retains its employees. Even if a firm aims to reorganize, many employees might leave after a bankruptcy filing to preempt getting fired in a liquidation. To help firms retain employees, the bankruptcy code allows firms to pay any wages that employees earn during bankruptcy. However, bankrupt firms cannot pay employees any pre-bankruptcy wages or benefits that were unpaid at the time of filing (Antill, Wang, and Jiang, 2024). Employees must wait with all other creditors until the end of the bankruptcy to receive payment for pre-bankruptcy obligations (11 U.S. Code §362). This can frustrate employees, motivating many firms to request special permission to pay these pre-bankruptcy employee obligations early. For example, when the nursing home chain Senior Care Centers filed for Chapter 11, it requested special permission to immediately pay employees their unpaid pre-bankruptcy wages. In its motion to the court, Senior Care Centers wrote:

> The Employees are critical to the Debtors' business, and their value cannot be

> overstated. To a significant extent, the long-term prognosis of the Debtors' patients depends on the Debtors' ability to attract and retain qualified personnel. The loss of certain Employees will impede the Debtors' business and seriously harm the ability to successfully implement their bankruptcy strategy... If the Debtors cannot assure their Employees that they will promptly pay the Employee Benefits Obligations... certain Employees will likely seek employment elsewhere. The loss of Employees at this critical juncture would have a material adverse impact on the Debtors' business.

Roughly four months into the bankruptcy, creditors successfully blocked this motion, preventing the employees from receiving payment. This is precisely when Senior Care Centers, which is in our data sample, experienced massive employee turnover. This case exemplifies the empirical findings of our study that bankruptcies lead to employee turnover that, in turn, leads to worsening care and harms to patients. Moreover, this example shows that employee departures might occur months after a bankruptcy filing.

Healthcare provider bankruptcies. There are a few features of healthcare and nursing home bankruptcies that are worth highlighting. First, Chapter 11 rarely leads to liquidation or closure for healthcare firms. In our sample, only 6% of bankrupt facilities close. Similarly, we find in Section 5 that facilities do not substantially reduce either patient volume or staffing levels. These facts imply that bankrupt nursing homes are likely fundamentally profitable and more valuable operating than in liquidation (11 U.S. Code §1129(a)7). This suggests that nursing home bankruptcies typically stem from excessive debt rather than incurable business-model flaws. The excessive debt levels might be explained by trends such as private equity activity (Gandhi, Song, and Upadrashta, 2022; Gupta et al., 2024) and asset tunneling (Gandhi and Olenski, 2024). Note that while risks of closure may be objectively low for nursing homes, staff may not be aware of this. Indeed, in response to our surveys (Section 7) nursing home workers frequently reported concerns about closures and degrading quality of employment.

Second, bankruptcy-induced staff separation could be quite costly for healthcare firms and their patients. Healthcare staff must be experienced and familiar with a facility and its patients' healthcare needs to provide effective care. This is especially true for nursing homes, where care entails frequent interactions with patients whose memory or cognition may be highly limited and whose frailty means that adverse outcomes may be quite severe.

Third, as noted earlier, private equity firms have acquired many nursing homes through

debt-financed transactions. High levels of debt can lead to bankruptcy, and existing research has shown that private equity ownership affects nursing home operations (Gandhi, Song, and Upadrashta, 2022; Gupta et al., 2024). This raises the possibility that private equity ownership is an omitted variable in our analysis. However, this concern is unlikely to affect our results, as private equity acquisitions typically occur more than a decade before bankruptcy filings. In fact, in 96% of the bankruptcies in our sample, no private equity acquisition took place within the 10 years preceding the filing. Figure D3 provides further details. These patterns suggest that any effects of private equity ownership manifest well before the time frame we examine around each bankruptcy.

3 Conceptual Framework

We estimate the impacts of a healthcare provider filing for bankruptcy. What is the counterfactual to filing for bankruptcy? What does this counterfactual imply for the interpretation of our DiD exercise? In what sense do these bankruptcies create deadweight losses and what can policy makers do about these losses? To answer these questions, we introduce an informal model of the decisions that lead to a bankruptcy filing.

Our informal model begins with the decision of whether to rely heavily on debt financing (high leverage). Choosing low leverage makes a bankruptcy filing unlikely. However, leverage can create value for a firm in a number of ways, including by reducing tax burden (interest payments on debt are tax deductible), strengthening performance incentives for managers (Jensen, 1986), making asset value inaccessible to malpractice claimants (Gandhi and Olenski, 2024), and aiding in the negotiation of favorable reimbursement rates (Liu, 2021). Further, many acquirers require substantial debt financing to purchase healthcare providers.

If a firm chooses high leverage, it might become sufficiently profitable that it has no problem paying its debt. However, if it is unable to attain sufficient profitability, then it might become "financially distressed:" it struggles to pay interest on its debt and has difficulty repaying or refinancing its debt principal when it comes due. Even if a firm can pay its debt, being perceived as financially distressed can be costly. For example, potential employees might be deterred from applying for a job at a company that is perceived as distressed.

Once a firm experiences financial distress, it can choose to file for bankruptcy. In a successful reorganization, the firm can reduce its debt obligations, relieving financial distress

(Section 2.2). However, a bankruptcy filing can be quite costly if it makes distress more salient to a firm's employees, triggering employee departures. Consistent with a bankruptcy increasing the salience of distress, Antill and Hunter (2021) show that a bankruptcy filing dramatically increases awareness of a firm's distress.

A firm that wishes to continue operating while avoiding formal bankruptcy has two options. First, it can attempt to renegotiate its debt out of court. This approach is rarely successful: most debt restructurings are quickly followed by bankruptcy filings (Donaldson et al., 2020). Second, it can defer bankruptcy and gamble that its profits will grow. While firms that intend to file for bankruptcy often do so before exhausting their cash reserves——ensuring they have funds to operate during bankruptcy and negotiate with lenders——a firm determined to avoid bankruptcy may instead continue operating in financial distress. By doing so, it buys time to improve operations and generate enough profit to repay its debts without filing. However, if this approach fails, the firm risks entering bankruptcy later with minimal cash reserves.

Finally, once a firm files for bankruptcy, it will either reorganize, liquidate, or be acquired. Healthcare firms typically avoid liquidation (Section 2.2). However, employees might mistakenly believe that the risk of liquidation is high, scaring them into quitting prematurely. In this sense, a bankruptcy filing can be quite costly. While other facilities hire the departing employees, the facility-specific knowledge these employees obtained at the bankrupt facility is not transferable.

We now use this informal model to clarify our empirical approach.

What is the counterfactual to filing for bankruptcy? A firm that wishes to avoid bankruptcy can delay filing and hope that its conditions improve. Alternatively, the firm could avoid the risk of bankruptcy entirely by never choosing high leverage in the first place.

What comparison does our DiD estimate capture? In Section 5, we compare bankrupt firms to matched control firms that never file for bankruptcy. We compare each treated bankrupt firm to control firms in the weeks around bankruptcy. Mapping this to our informal model, some of our treated firms move quickly from financial distress to bankruptcy, while others file for bankruptcy after deferring as long as possible. All of our control firms avoided bankruptcy entirely, either through low leverage or good luck. Over a short time horizon, we assume that the changes experienced by the nonbankrupt control firms are comparable to the changes that the distressed firms would have experienced in the absence of a bankruptcy. Under this assumption, our DiD captures the impact of moving from financial

distress to bankruptcy, relative to a counterfactual of continued distress.

Is bankruptcy-induced staff turnover a deadweight loss or a transfer? In many cases, nurses who leave a bankrupt facility are hired at other facilities. In this sense, one might conjecture that any bankruptcy-induced staff turnover is simply a transfer from bankrupt to nonbankrupt facilities. However, the literature on nursing-staff tenure (Section 2.1) suggests that this conjecture is incorrect. Specifically, nurses develop facility-specific human capital as their tenure at a specific facility grows. In this sense, nurse experience is not fully transferable across facilities, which is why nurse *tenure* is used in regulatory quality measures (Section 2.1). Thus, bankruptcy-induced staff turnover is a deadweight loss in the sense that it destroys facility-specific human capital.

How could a policy maker prevent costly bankruptcies? A policymaker who wants to avoid bankruptcy filings could limit the leverage of healthcare firms. Alternatively, the policy maker could provide subsidies or conditional support to increase the likelihood of recovering from financial distress. Such a subsidy would incentivize firms to defer filings and potentially prevent some filings entirely. Finally, a policy maker could make a more radical change to the bankruptcy process for healthcare providers. For example, when a bank becomes insolvent, regulators immediately take control of the bank and find a healthy bank to acquire the insolvent bank's assets as quickly as possible. In theory, the same regulatory process could be applied to healthcare providers.[2]

4 Administrative Data

4.1 Nursing Home Data

Payroll Based Journal. Starting in the fourth quarter of 2016, CMS required nursing homes to submit daily staffing records for all workers—including both employees and contract workers—engaged in direct resident care. To ensure accuracy, submissions are required to be based on payroll and other auditable data. Correspondingly, these records are known as the Payroll-Based Journal (PBJ).

We obtained the PBJ from CMS via two federal FOIA lawsuits (Gandhi v. Centers for Medicare & Medicaid Services, 2019 and 2020).We use the records to observe the hours

[2]Any policy limiting bankruptcy filings would have ex-ante implications for borrowers, as shown empirically by Gross et al. (2021) and theoretically by Antill and Grenadier (2019).

worked by each nursing staff member on each day during our sample. In total, our dataset contains 1.1 billion staffing shifts for 7.5 million different employment relationships. Each record details the worker's facility-specific identifier, their job (e.g., RN, LPN, or CNA), whether they are an employee or a contractor, and the precise amount of time they worked on a given day.

We analyze all RN, LPN, and CNA records from 2016Q4 through 2020Q1. We do not extend our sample past 2020Q1 for two reasons related to the COVID-19 pandemic. First, CMS briefly paused reporting requirements at the start of the pandemic in order to reduce the reporting burden on an industry in crisis. Second, the COVID-19 pandemic affected nursing home staff in dramatic and unprecedented ways. Variation in staffing during the pandemic was likely predominantly attributable to pandemic-induced strains, such as outbreaks (Shen et al., 2022) or vaccination mandates (Gandhi et al., 2024a). Moreover, the federal and state governments infused the industry with many billions of dollars in aid—including $21 billion earmarked in the CARES Act (Soergel, 2020)—to prevent facilities from becoming insolvent.

Health inspection data. We utilize detailed data from CMS on unannounced health inspections at each facility. Professional health inspectors employed by the state conduct unannounced inspections at each facility to assess whether it meets federal requirements. On average, inspections occur approximately annually, and the gap between inspections should not exceed fifteen months. Facilities are penalized for deficiencies that indicate noncompliance with federal standards. The inspections focus on facility practice and policy in a number of areas, including quality of care, resident rights, and physical environment. Inspectors also categorize the severity and scope of each deficiency. Levels of severity range from "no actual harm with potential for minimum harm" to "immediate jeopardy to resident harm or safety." A deficiency's scope can be either isolated, pattern, or widespread. We also utilize CMS' categorization of citations into broad areas, such as nursing, quality of care, or physical environment in our analysis.

Nursing home characteristics. We use Brown's LTCFocus database to obtain annual data on nursing homes' characteristics. These include facilities' for-profit status, certified bed capacity, occupancy, and fraction of care-days reimbursed by Medicare.

4.2 Patient Data

In this section, we describe the three linked administrative datasets from CMS that we use to observe virtually all patients at nearly every nursing home from 2010 through 2019.

Medicare enrollment files. Our first dataset is the Master Beneficiary Summary File (MBSF). This dataset covers all Medicare beneficiaries. For each beneficiary in each month, the MBSF provides a record of their enrollment status (e.g., whether the beneficiary is enrolled in Traditional Medicare, Medicare Advantage, or Medicaid). The dataset also includes a rich set of patient demographic variables, such as sex, age, race, and ZIP code of residence (at the yearly level). Additionally, the MBSF also tracks chronic conditions, including Alzheimer's, anemia, cancer, diabetes, asthma, stroke, rheumatoid arthritis, hip fracture, osteoporosis, depression, cataracts, glaucoma, chronic kidney disease, atrial fibrillation, chronic obstructive pulmonary disease, ischemic heart disease, acute myocardial infarction, congestive heart failure, hyperplasia, hypertension, hyperlipidemia, and hypothyroidism.

Medicare claims. When a Medicare beneficiary receives medical care, the healthcare provider files a claim with Medicare. The claim includes detailed information regarding the care that the patient received, including procedures, diagnosis codes, dates of care provision, and the amount charged by the provider. We obtain cleaned Medicare claims data derived from the Medicare Inpatient (IP) Claims file, Medicare Outpatient (OP) claims file, and the Medicare Provider Analysis and Review (MedPAR) files. The Medicare IP and OP files provide raw claim data, and the MedPAR file provides an aggregation of inpatient claims to the episode level. These data provide detailed care descriptions for all inpatient and outpatient Medicare claims. They also allow us to observe the amount, type, and cost of care that Traditional Medicare enrollees received at their nursing homes. The hospital claims data also allow us to observe additional information on residents' diagnoses that may have led to their nursing home stays. These data also allow us to observe when residents are admitted to the emergency department or rehospitalized (i.e., they return to the hospital after being admitted to a nursing home). Because the healthcare claims associated with Medicare Advantage patients are not observed, these claims are excluded from our analyis of the claims data.

Resident health assessments. Federal regulations require nursing homes to regularly submit detailed health assessments for each resident to CMS.[3] Nursing homes must submit specific assessments for each resident, regardless of that resident's type of insurance, at admission, discharge, or major change in status, as well quarterly and annually. Additionally, for any stay reimbursed by Medicare, the facility must file additional Medicare Prospective Payment System assessments on or around 5, 14, 30, 60, and 90 days from admission, as well as assessments at the time of any readmission or significant clinical change.

We access data from these assessments through the Long Term Care Minimum Data Set (MDS) version 3.0. These MDS assessments provide detail on each resident's health during the assessment period, including their physical ailments, mental and cognitive wellbeing, and chemical and physical restraints.

4.3 Bankruptcy Data

The Public Access to Court Electronic Records (PACER) service provides electronic public access to federal court records. Established in 1988, the PACER system has grown to provide virtually universal coverage of federal cases. Today, it provides "nearly all the documents filed by a judge or the parties in any case." Since bankruptcy courts are federal courts, PACER contains detailed information on every bankruptcy case.

Since 2008, the Federal Judicial Center (FJC) has publicly provided a dataset covering every case filed in the PACER system. The FJC provides some variables for each case, including an indicator equal to one in all bankruptcies involving a healthcare company ("healthcare bankruptcies").[4] We use this indicator to create a dataset containing all Chapter 11 healthcare bankruptcies. Using the FJC's numeric case identifiers, we locate each bankruptcy in PACER and download comprehensive case information for each healthcare bankruptcy. Notably, for each bankruptcy, we obtain the bankruptcy filing date and identifying information such as the name, address, and employer-identification number (EIN) for the bankrupt company. We merge our bankruptcy data with our CMS data using EINs, names, and addresses. Specifically, through a Freedom of Information Act request, we obtain a novel dataset containing the EIN for every healthcare provider in the National Plan and Provider Enumeration System (NPPES) database. We also obtain EINs for parent companies, allowing us to observe each subsidiary of a bankrupt parent company. In this way, we identify

[3]See https://www.gao.gov/assets/hrd-87-113.pdf

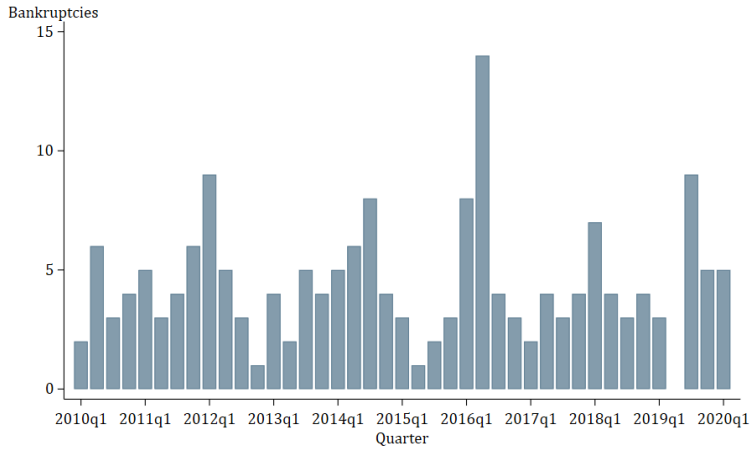
[4]Corporate Chapter 11 filing petitions include a line requiring filers to disclose if the bankruptcy involves a healthcare company.

which healthcare facilities in the CMS data file for Chapter 11 bankruptcy. See Appendix B for details.

We also use our PACER data to group together healthcare facilities that share a parent company (i.e., facilities that are in the same chain). Our final dataset contains all bankruptcies filed over the period 2010Q1-2020Q1.

Figure 1 illustrates the number of nursing home bankruptcies at the chain level during the sample period, which includes 180 chain bankruptcies, representing 727 facilities. The frequency of bankruptcies is fairly similar across the sample period.

Figure 1: Nursing Home Chain Bankruptcy Frequency: 2010 Q1 - 2020 Q1



Note. This figure plots the number of bankruptcies filed by nursing home chains (on the y axis) in each quarter (on the x axis) over the period from 2010 Q1 to 2020 Q1.

5 Employment Responses to Bankruptcy

In this section, we use a difference-in-differences (DiD) approach on high-frequency employment data to quantify how filing for Chapter 11 bankruptcy impacts a facility's employment.

5.1 Empirical Strategy: Matched Differences-in-Differences

Matching. For each "treated" facility that files for Chapter 11 during our sample period (Section 4.3), we identify up to five observably similar "control" facilities that do not file for

bankruptcy during our sample period.[5] To identify facilities that were observably similar to the treated facility in the year prior to bankruptcy, we perform a coarsened exact matching without replacement. Specifically, we require candidate controls to exactly match the treated facility on deciles of (i) the number of certified beds, (ii) the average fraction of occupied beds (the "occupancy rate"); and (iii) the share of the facility's patients whose care is reimbursed by Medicare.[6] This matching ensures that treated facilities are compared to controls that are similar in size, bed utilization, and patient characteristics.

[5]When more than five facilities are eligible controls, we randomly select five eligible controls.

[6]Most nursing homes provide both post-acute rehabilitative and therapy care—which is covered by Medicare—and long-term care, which is not covered by Medicare but is covered by Medicaid and some private insurance. As such, the share of a facility's residents whose care is reimbursed by Medicare is a common measure of the extent to which the facility provides post-acute versus long-term care.

Table 1: Balance Table

	(1) Treated Facilities	(2) Control Facilities	(3) |Diff|/SD
Match Variables			
Certified Beds	122.22	125.06	0.05
	(39.71)	(53.43)	
Occupancy Rate	79.11	78.79	0.02
	(14.89)	(14.63)	
Percent Medicare	14.52	14.25	0.02
	(9.92)	(10.93)	
Employment Outcomes (Weekly; Per 100 Beds)			
Hires	1.46	1.34	0.05
	(1.91)	(2.53)	
Separations	1.32	1.24	0.04
	(1.54)	(1.90)	
Hours			
All Workers	1970.63	2058.81	0.14***
	(511.12)	(642.61)	
$\geq$ 60 Days Tenure	1370.80	1425.90	0.07
	(683.87)	(789.53)	
$<$ 60 Days Tenure	599.83	632.91	0.05
	(544.06)	(662.54)	
Percent of Hours			
$\geq$ 60 Days Tenure	68.54	68.31	0.01
	(28.44)	(30.08)	
$<$ 60 Days Tenure	31.46	31.69	0.01
	(28.44)	(30.08)	
N	481	2,257	2,738

Note. We match each bankrupt (treated) facility to a group of facilities that never file for bankruptcy (controls). This table compares treated facilities to control facilities. For each variable, we present its mean for treated and control facilities in columns (1) and (2), respectively. Variables are measured 52 weeks before each treated facility's bankruptcy. We present standard deviations in parentheses. In column (3), we present the absolute value of the difference between the means in columns (1) and (2), normalized by the control-group standard deviation. We indicate the statistical significance of this difference at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Table 1 compares treated and control facilities in the year prior to bankruptcy. They are quite similar across the variables used in matching. Treated and control facilities are also similar across employment measures such as average employee tenure and the number of hires and separations. The notable exception is total staffing hours, which are are slightly greater in the control group. However, this difference is only a small fraction of the standard deviation of total staffing hours. More importantly, as we discuss below, differences between treated and control facilities do not necessarily violate our identifying assumption.

DiD specification. We estimate the effect of bankruptcy via the following DiD regression estimated on a facility-week panel:

$$\begin{aligned} y_{f,w} = & \underbrace{\delta}_{\text{Early Pre-Period}} \cdot 1\{w < T_{c(f)} - 52\} \cdot B_f \\ & + \underbrace{\beta^S}_{\text{Short-Term Effect}} \cdot 1\{T_{c(f)} \leq w \leq T_{c(f)} + 52\} \cdot B_f \\ & + \underbrace{\beta^L}_{\text{Long-Term Effect}} \cdot 1\{w > T_{c(f)} + 52\} \cdot B_f + \alpha_{w,c(f)} + \rho_{f,c(f)} + \epsilon_{f,w}, \end{aligned} \tag{1}$$

where $y_{f,w}$ is an outcome, such as staff hours, at facility f in match cohort $c(f)$ in week w. B_f denotes an indicator for facilities that file for bankruptcy during the sample period. $T_{c(f)}$ denotes the week in which the treated facility f in the cohort $c(f)$ files for bankruptcy. Importantly, we include cohort-specific facility fixed effects $\rho_{f,c(f)}$ and cohort-by-week fixed effects $\alpha_{w,c(f)}$.[7] In this sense, we conduct a *stacked* DiD (Cengiz et al., 2019) robust to issues stemming from heterogeneous dynamic treatment effects and variation in treatment timing (Goodman-Bacon, 2021).

Equation (1) distinguishes the short-term and long-term effects of a bankruptcy filing. To do this, we distinguish four periods for each cohort c: (i) the period more than one year before the treated facility files ($w < T_{c(f)} - 52$); (ii) the year immediately prior to the filing ($T_{c(f)} - 52 \leq w < T_{c(f)}$); (iii) the year immediately after the filing ($T_{c(f)} \leq w \leq T_{c(f)} + 52$); and (iv) the period more than one year after the filing ($w > T_{c(f)} + 52$).[8] We use (ii) the year immediately prior to filing as the omitted reference period so that δ, β^S, β^L each capture a comparison between treated and control facilities in periods (i), (iii), and (iv) relative to the

[7] Facility-by-cohort fixed effects are equivalent to facility fixed effects since matching is without replacement.

[8] We include cohorts in which the bankruptcy filing occurs in the first 52 weeks or last 52 weeks of our sample. This results in an unbalanced panel but allows us to maximize our sample size.

reference period. The key parameters of interest are β^S and β^L, which respectively capture the short-term and long-term effects of bankruptcy.[9]

To visualize the high-frequency dynamic effects of a bankruptcy at the weekly level, we estimate the following DiD event study:

$$y_{f,w} = \sum_{\tau \neq -1} \beta_\tau \cdot 1\{w = T_{c(f)} + \tau\} \cdot B_f + \alpha_{w,c(f)} + \rho_{f,c(f)} + \epsilon_{f,w} \tag{2}$$

For any $\tau \geq 0$, β_τ captures a comparison between treated and control facilities τ weeks after a bankruptcy filing, relative to the week prior to the filing. For $\tau < -1$, β_τ captures an analogous comparison $|\tau|$ weeks before the filing.

We cluster standard errors at the nursing home chain level since bankruptcy filings typically encompass all facilities within a chain (Abadie et al., 2023).

Identification. The standard identifying assumption for DiD is that in the absence of treatment, the treated and control facilities would have experienced parallel trends in their outcomes. In our setting, this means that we assume that bankrupt facilities would have experienced similar staffing changes to matched non-bankrupt facilities in the absence of bankruptcy filings. The assumption could be violated if unobservable economic shocks cause both bankruptcy filings and staffing changes. Our empirical design addresses this concern in two ways. First, we use matched controls of similar size, bed utilization, and patient composition to treated facilities. This makes it plausible that our control facilities faced similar operational circumstances. Second, we exploit the high-frequency nature of our weekly dataset to isolate the effect of a bankruptcy filing from the general effect of any unobserved conditions that might have lead to a bankruptcy. Insofar as the effects on staffing occur in the immediate weeks and months after filing, such sharp effects are unlikely to be attributable to general differential trends.

5.2 Occupancy, Staffing, and Skill Mix

In this section, we discuss the effects of bankruptcy on facilities' occupancy, staffing levels, and skill mix. Table 2 presents our DiD estimates (equation 1) of the short-term and long-term effects of bankruptcy. Figure C5 presents the associated high-frequency event studies (equation 2), focusing on the year immediately prior to the filing and the year after the filing.

[9] We distinguish (i) from (ii) principally to ensure the reference period best represents facilities immediately prior to the bankruptcy filing.

Table 2: The Effect of Bankruptcy on Occupancy, Staffing Levels, and Skill Mix

	Resident-Days	Hours	Employees	RN Hour Share	LPN Hour Share	CNA Hour Share
$0 \leq t \leq 52$	-6.090	-14.458	-0.423	0.198	-0.090	-0.108
	(5.044)	(11.298)	(0.390)	(0.236)	(0.151)	(0.222)
$t \geq 53$	-6.148**	-42.501***	-1.278***	-0.236	0.268	-0.032
	(3.090)	(14.492)	(0.412)	(0.491)	(0.289)	(0.272)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.97	0.89	0.89	0.74	0.80	0.68
Mean	675.22	2,052.42	63.19	16.25	23.72	60.03
Observations	503,125	516,072	516,072	516,072	516,072	516,072

Note. Each column of this table presents results from estimating equation (1) using a different dependent variable. The dependent variables from left to right are: total weekly patient occupancy (resident-days), total weekly hours per 100 beds, total number of employees working at the facility in a given week per 100 beds, and the share of weekly hours provided by RNs, LPNs, and CNAs, respectively. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

Occupancy. We measure facility occupancy at the facility-week level using "resident-days:" we calculate the number of patients residing at the facility each day, then we sum over all days in a given week. We estimate equation (1) using resident-days as the outcome variable and present the results in the first column of Table 2. Our estimate of the short-term effect of bankruptcy is both extremely small ($< 1\%$ of the dependent-variable sample mean) and statistically insignificant. Similarly, the high-frequency event study (panel a of Figure C5) suggests only a very small effect within a year of the bankruptcy filing. While we estimate a statistically significant effect of bankruptcy on long-term occupancy, the magnitude of the treatment effect is quite small ($< 1\%$ of the dependent-variable sample mean). In this sense, our estimates imply that bankruptcies do not lead facilities to meaningfully reduce the volume of patients that they serve in either the short term or long term.

Staffing levels. We measure facilities' weekly staffing levels in two ways: (i) the total number of hours worked by nursing staff that week, and (ii) the total number of employees who worked any hours that week. To ease interpretation and comparison across facilities of varying sizes, we normalize these staffing measures to be "per 100 beds."[10] We choose

[10]Specifically, we first define a scaling factor by dividing the total number of beds by 100. Then, we adjust each staffing measure by dividing it by this scaling factor.

100 because the typical facility has approximately 100 certified beds. In the second and third columns of Table 2, we present results from estimating equation (1) using these two staffing measures as outcome variables. As with occupancy, we find very small (<1% of the dependent-variable sample means) and statistically insignificant short-term effects on both hours and employees. Likewise, the event studies (panels b and c of Figure C5) show only small effects by the end of the first year after bankruptcy. While the long-term effects are statistically significant for both hours and employees, the magnitudes of these treatment effects are relatively small (approximately 2% of the dependent-variable sample means). These estimates indicate that bankruptcies do not result in immediate or dramatic reductions in total staffing levels.[11]

Skill mix. There is considerable variation in the level of training required for different nursing staff roles. On one end of the spectrum, training as an RN requires multiples years of education, while CNA certification can sometimes be completed in a matter of weeks. We examine whether bankruptcy results in a shift in staff "skill mix" by estimating the impact of bankruptcy on the share of RNs, LPNs, and CNAs. For each nursing role and each facility-week observation, we calculate the share of all nurse hours that are associated with that nursing role. In the fourth, fifth, and sixth columns of Table 2, we present results from estimating equation (1) using these three nursing role share variables as dependent variables. In all cases, our estimates suggest no statistically significant effects on either short-term or long-term skill mix, as captured by nursing role shares. Likewise, the event studies show no dynamic effects in the first year after bankruptcy (panels d, e, and f of Figure C5).

In summary, our estimates suggest that facilities maintain overall occupancy, staffing levels, and nursing role composition following a Chapter 11 filing. There may, however, be other ways in which bankruptcies affect staffing and operations. In the next section, we examine the effect of bankruptcies on turnover and staff tenure.

5.3 Turnover and Tenure

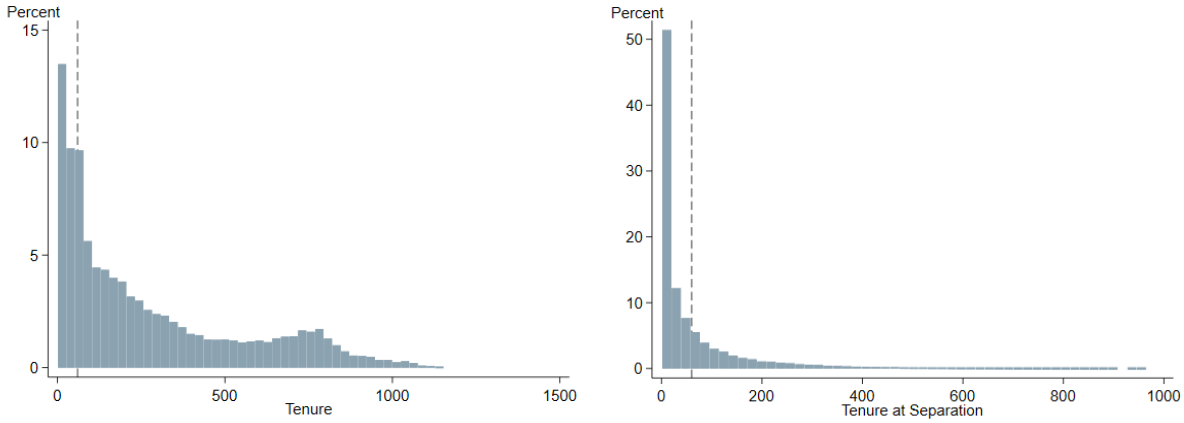
The tenure of a nursing home's staff is a critical determinant of nursing home quality (Section 2.1). We now show that bankruptcies reduce the average staff tenure at bankrupt

[11] Moreover, any slight reduction in long-term staffing levels are also met with a slight reduction in long-term occupancy. As a result, effects on staffing levels per resident—a common measure of quality of care—are even more muted.

facilities through turnover: workers leave and facilities hire new workers to replace them.

Measuring staff tenure. The detailed nature of our data allows us to measure the tenure of each staff member working at each facility in each week. Figure 2a presents the distribution of nursing staff tenure, using a sample that includes all shifts worked in the last year of our sample. Figure 2b presents the distribution of tenure for a different sample, which includes only the last shift worked by each worker at a given facility. In our analysis, we distinguish low-tenure staff (i.e. new staff) as those who have worked fewer than 60 days at a facility. This cutoff corresponds to approximately the 25th percentile of employee tenure, which is 59 days. Appendix C.5 demonstrates the robustness of our results to alternative definitions of low-tenure staff. In any turnover-related regression, we only include facility-week observations in which the facility reports in the 13 weeks ($\approx$ 90 days) prior. This allows us to accurately measure whether a worker has 60 days of experience at a facility.

Figure 2: Employee Tenure



(a) Distribution of Tenure

(b) Distribution of Tenure at Separation

Note. This figure plots the distribution of staff tenure: the number of days that a particular staff member has worked at a particular facility. In panel a, the sample includes all shifts in 2019. We focus on 2019 to minimize the number of staff whose tenure is censored by the start of the sample. We plot the percentage of workers (on the y axis) with a particular number of days of tenure (on the x axis). The vertical dashed line denotes the 25th percentile, which is 59 days. In panel b, the sample includes all terminal shifts: the last shift worked by a worker at a particular facility.

Staff turnover results. We show that a bankruptcy filing leads to increased staff turnover, which in turn reduces the overall level of staff tenure at a bankrupt facility. We show this

result in two steps. First, we show that turnover increases after a bankruptcy filing. We estimate equation (1) using a measure of worker exits as the outcome variable. Specifically, the dependent variable is the number of workers exiting a facility in a given week, identified using the last shift that a worker works at a facility, per 100 beds. The second column of Table 3 displays the results. The weekly number of worker exits per 100 beds spikes by 0.146 in the year after a bankruptcy filing (10.3% of the sample mean). In the long-term (more than one year after the filing), the weekly number of worker exits is 0.123 higher at bankrupt facilities (8.7% of the sample mean). Both of these treatment effects are strongly statistically significant, with nursing home-chain clustered standard errors of 0.034 and 0.038, respectively.

Next, we show that departing workers are replaced by new hires. We estimate equation (1) using an outcome variable that measures new hires: the number of new workers starting at a facility in a given week, identified using each worker's first shift at a given facility, per 100 beds. The first column of Table 3 displays the results. We find an economically and statistically significant increase in new worker hires after a bankruptcy filing. The weekly number of new hires per 100 beds spikes by 0.118 in the year after a bankruptcy filing (8.7% of the sample mean) and increases by 0.146 (10.8% of the sample mean) in the long term. Importantly, the increase in new hires after a bankruptcy filing is of roughly the same magnitude as the increase in worker exits. This result explains our earlier finding that overall staffing levels remain roughly constant after a bankruptcy. In Figure C1, we corroborate this result by plotting weekly treatment-effect estimates, which we obtain by estimating equation (2) with the same outcome variables.

Finally, we exploit the detailed nature of our data to identify new hires and exits corresponding to each nursing role: RNs, LPNs, and CNAs. For each nursing role, we construct role-specific hire and exit variables that are analogous to the hire and exit variables defined above. Columns 3 and 4 of Table 3 show that RN turnover is minimal compared to the overall level of turnover. Columns 5 and 6 show higher levels of turnover for LPNs. Columns 7 and 8 show that CNAs experience the greatest amount of turnover.

Staff tenure results. How does the documented turnover affect the amount of care provided by high-tenure staff with facility-specific experience? In the second step of our analysis, we answer this question. We study how bankruptcy filings impact the amount of care provided by high-tenure workers. Specifically, we construct an outcome variable by summing the number of hours worked by high-tenure workers at a given facility in a given week. Following

Figure 2a, we consider a worker to have high tenure if they have worked at a facility for at least 60 days. We normalize this total number of hours by the number of beds divided by 100 to construct hours per 100 beds. We estimate equation (1) using this outcome variable and present the results in the first column of Table 4. The number of hours worked by high-tenure workers declines in the year after a bankruptcy and remains depressed for more than a year after a bankruptcy filing. The treatment effects are highly statistically significant.

For robustness, we repeat this exercise using two alternative measures of the amount of care provided by high-tenure workers. We divide the total number of high-tenure-worker hours by the total number of hours worked by any workers to construct a facility-week measure of the share of hours worked by high-tenure workers. We estimate (1) using this outcome variable and present the results in the second column of Table 4. We also construct an outcome variable by counting the number of high-tenure employees working at each facility in each week. We normalize by the number of beds divided by 100. We estimate (1) using the number of high-tenure workers per 100 beds as an outcome variable and present the results in the third column of Table 4. The results mirror the results of the first column, with statistically significant point estimates and slightly larger magnitudes. For example, the share of hours worked by high-tenure workers declines by two percentage points in the year after a bankruptcy filing (2.5% of the sample mean) and three percentage points in the long run.

As the share of hours worked by high-tenure workers falls, the share of hours worked by low-tenure workers must rise. To show this, we define three outcome variables that are analogs of the three outcome variables defined above, except that they capture the amount of hours worked by *low*-tenure workers (i.e., workers with fewer than 60 days of experience at a facility). In columns four to six of Table 4, we present results from estimating equation (1) using the following outcome variables: (i) the number of hours worked by low-tenure workers per 100 beds, (ii) the share of hours worked by low-tenure workers, which is simply one minus the dependent variable from column 2, and (iii) the number of low-tenure employees per 100 beds. As expected, we find that bankrupt firms rely more heavily on low-tenure workers as they replace departing workers with new hires.

Finally, we estimate equation (2) using the outcome variables described above to study the impacts of a bankruptcy filing at a higher frequency. In panel a of Figure 3, we present weekly treatment effects on the number of high-tenure workers per 100 beds. There is no observable pretrend prior to bankruptcy. In the weeks after a bankruptcy filing, the number of high-tenure workers falls. In panel b of Figure 3, we present weekly treatment effects

on the number of low-tenure workers per 100 beds. We find no pretrends. The number of low-tenure workers spikes in the weeks after a bankruptcy filing. In Appendix C.2, we repeat this exercise focusing on individual nursing roles (i.e., hours worked by high-tenure RNs). We find a shift in worker composition toward lower-tenure workers across staff roles. Bankruptcies appear to quickly impact worker tenure for RNs, who have the highest level of certification among nursing staff roles and have a key role in determining nursing home quality.

Table 3: The Effect of Bankruptcy on Nursing Staff Turnover

	All		RN		LPN		CNA	
	New Hires	Exits	New Hires	Exits	New Hires	Exits	New Hires	Exits
$0 \leq t \leq 52$	0.118**	0.146***	0.009	0.024***	0.035***	0.046***	0.077**	0.079***
	(0.046)	(0.034)	(0.008)	(0.007)	(0.008)	(0.008)	(0.032)	(0.025)
$t \geq 53$	0.146***	0.123***	-0.002	0.014*	0.043***	0.038***	0.103***	0.072**
	(0.055)	(0.038)	(0.012)	(0.008)	(0.009)	(0.009)	(0.037)	(0.029)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.37	0.42	0.27	0.28	0.30	0.32	0.34	0.38
Mean	1.35	1.42	0.19	0.21	0.26	0.28	0.89	0.92
Observations	459,804	459,804	459,804	459,804	459,804	459,804	459,804	459,804

Note. The dependent variable New Hires represents the number of new workers in a facility-week per 100 beds. The dependent variable Exits represents the number of exiting workers in a facility-week per 100 beds. The results are shown for all nursing staff, RNs, LPNs, and CNAs, respectively. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

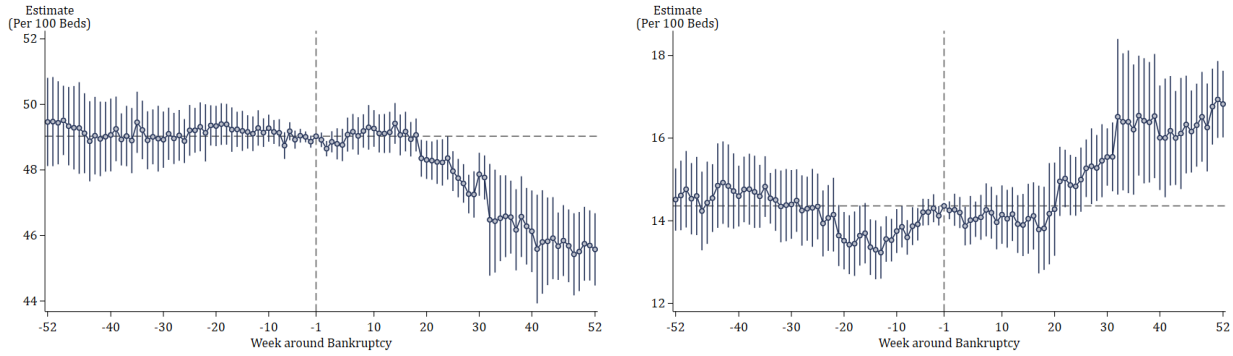
Table 4: The Effect of Bankruptcy on the Tenure of Nursing Staff

	$\geq$ 60 Days Tenure			$<$ 60 Days Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
$0 \leq t \leq 52$	-44.913***	-2.054***	-1.420***	29.300***	2.054***	0.937***
	(14.248)	(0.482)	(0.463)	(9.134)	(0.482)	(0.309)
$t \geq 53$	-96.082***	-3.262***	-3.160***	48.270***	3.262***	1.741***
	(13.010)	(0.710)	(0.474)	(14.841)	(0.710)	(0.599)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.53	0.87	0.58	0.53	0.63
Mean	1,692.67	81.66	49.03	363.12	18.34	14.36
Observations	459,804	459,804	459,804	459,804	459,804	459,804

Note. This table examines staffing by high-tenure and low-tenure workers. The dependent variable Hours represents weekly hours worked by high-tenure or low-tenure workers, per 100 beds. The dependent variable Hour Share represents share of total weekly hours worked by high-tenure or low-tenure workers. The dependent variable Employees represents number of high-tenure or low-tenure employees per 100 beds. Each observation is a facility week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Additional results. Finally, two pieces of evidence imply that bankrupt nursing homes incur greater labor costs. First, we show that nursing homes switch from wage-earning employees ("wage workers") to more expensive contract workers. Specifically, we define an outcome variable equal to the number of hours worked by wage workers per 100 beds. We estimate equation (1) using this outcome variable and present the results in the first column of Table 5. Bankrupt firms rely less on wage workers in the year after a bankruptcy filing and the effect continues in the long term. We find similar results when we use alternative measures of wage-worker prominence: the share of hours worked by wage workers and the number of wage workers per 100 beds. As wage workers leave, bankrupt firms replace them with contract workers. To show this, we estimate (1) using the number of hours worked by contract workers, per 100 beds, as an outcome. The fourth column of Table 5 shows a rise in contract-worker hours after a bankruptcy filing. The concurrent increase in the share of hours worked by contract workers is statistically and economically significant: the short-term treatment effect of 0.781 is 32% of the dependent-variable sample mean. Since contract workers tend to be far more costly than wage workers, this shift toward contract workers suggests that bankrupt facilities incur greater labor costs after filing for bankruptcy. Second, in Appendix C.3, we directly show that the average hourly nursing wage rises by 2% after a bankruptcy filing.

Figure 3: Dynamic Effects of Bankruptcy on Nursing Staff Tenure



(a) $\geq$ 60 Days Tenure Workers

(b) $<$ 60 Days Tenure Workers

Note. We estimate the dynamic difference-in-differences specification (2) to calculate bankruptcy treatment effects in each week around the filing date. In each panel of this figure, we plot the treatment-effect estimates (on the y axis) for each week (on the x axis) around the bankruptcy filing. In panel (a), the dependent variable is the number of workers with at least 60 days of experience at the facility per 100 beds. In panel (b), the dependent variable is the number of workers with fewer than 60 days of experience at the facility per 100 beds. We calculate standard errors for each treatment-effect estimate, clustering by nursing home chain. The vertical line covering each estimate displays a 95% confidence interval. The vertical dashed line marks one week before the bankruptcy filing. See Table 4 for point estimates. See Appendix C.2 for tenure changes for each nursing staff role.

It would be puzzling for a bankrupt nursing home to simultaneously fire employees and increase wages. In this sense, the fact that nursing homes pay higher wages after a bankruptcy filing suggests that worker departures are voluntary (workers quitting) rather than involuntary (worker firings). We confirm this with survey evidence in Section 7.

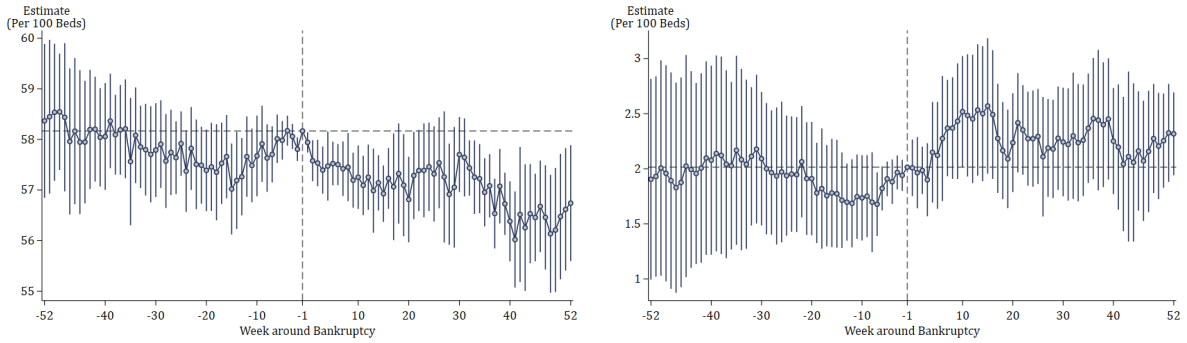
In summary, we exploit detailed high-frequency staffing data to estimate the causal effect of a bankruptcy filing on nursing home staffing. Our stacked matched cohort DiD approach reveals that bankrupt facilities maintain total staffing levels. However, bankrupt facilities experience heightened worker turnover in the weeks after a bankruptcy filing. This turnover leads to a substantial increase in the share of low-tenure workers who are unfamiliar with the bankrupt facility. Departures appear to be initiated by workers because: (1) exiting workers are quickly replaced by new hires, (2) facilities shift to costlier contract labor, and (3) RN wages increase.

Table 5: Staffing Responses to Bankruptcy by Employment Contract

	Wage Workers			Contract Workers		
	Hours	Hour Share	Employees	Hours	Hour Share	Employees
$0 \leq t \leq 52$	-24.210**	-0.824***	-0.758**	8.288**	0.781***	0.340*
	(11.597)	(0.260)	(0.340)	(3.895)	(0.196)	(0.178)
$t \geq 53$	-52.756***	-1.009*	-1.596***	13.197**	1.035***	0.490***
	(11.618)	(0.541)	(0.374)	(5.571)	(0.354)	(0.175)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.58	0.88	0.66	0.56	0.66
Mean	1,901.76	92.40	58.17	41.80	2.45	2.01
Observations	516,072	516,072	516,072	516,072	516,072	516,072

Note. This table examines staffing by wage-earning employees (wage workers) and contract workers. The dependent variable Hours represents weekly hours worked by wage workers or contract workers, per 100 beds. The dependent variable Hour Share represents share of total weekly hours worked by wage workers or contract workers. The dependent variable Employees represents number of wage workers or contract workers per 100 beds. Each observation is a facility week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Figure 4 for event studies.

Figure 4: Staffing Responses to Bankruptcy by Employment Contract



(a) Wage Workers

(b) Contract Workers

Note. We estimate the dynamic difference-in-differences specification (2) to calculate bankruptcy treatment effects in each week around the filing date. In each panel of this figure, we plot the treatment-effect estimates (on the y axis) for each week (on the x axis) around the bankruptcy filing. In panel (a), the dependent variable is the number of wage workers per 100 beds. In panel (b), the dependent variable is the number of contract workers per 100 beds. We calculate standard errors for each treatment-effect estimate, clustering by nursing home chain. The vertical line covering each estimate displays a 95% confidence interval. The vertical dashed line marks one week before the bankruptcy filing. See Table 5 for point estimates.

6 Quality of Care and Patient Health

In the previous section, we showed that a nursing home's bankruptcy filing causes worker turnover and a shift toward low-tenure workers. Given the intimate and labor-intensive nature of nursing home care, these changes to staffing could meaningfully affect patient care. To explore this possibility, we use data from nursing home inspections to determine whether facilities are more likely to be cited for violating health and safety codes after bankruptcy. Additionally, we use administrative patient health data from Medicare claims and assessments to study the impact of bankruptcy on patients' health outcomes.

6.1 Health Inspections

Background. CMS requires all states to regularly inspect all nursing homes. These "standard inspections" (Section 2) must be conducted at an average rate of once every twelve months. Standard inspections are unannounced and extremely thorough, with the median inspection team taking four days to evaluate a facility for approximately 200 possible violations. Inspectors observe operations and perform interviews to ascertain facilities' practices and policies in areas such as nursing services and residents' quality of care and physical environment. The average inspection results in more than six citations (also called "deficiencies"). In addition to standard inspections, inspectors sometimes visit a facility in response to resident complaints. These "complaint inspections" can lead to additional citations ("complaint deficiencies"). On average, facilities receive approximately two complaint deficiencies between each standard inspection.

Inspections can reveal many types of violations. Some citations relate broadly to the "quality of care," as captured by metrics that CMS defines. For example, inspectors give a citation for unnecessarily feeding residents through a tube or otherwise failing to provide services that would allow a tube-fed resident to return to oral eating. Tube feeding frequently contravenes clinical recommendations (Mitchell et al., 2016) but persists because it saves money and staff time (Mitchell et al., 2004). Another citation relates to the inappropriate or unnecessary use of bedrails, which risk entrapping patients in their beds.

Other citations given by inspectors relate specifically to the quality of the nursing services (Centers for Medicare & Medicaid Services, 2021). For example, one citation is given by inspectors when they determine that the facility's staffing is "insufficient" to care for its residents. Another is given for failing to provide CNAs with performance reviews and related in-service training. This represents a major failure in the human resource process. CNAs

make up 60% of facility staff and the CNA certification can be completed in as little as a month. In-service, on-the-job training is therefore an important factor affecting the quality of CNA care (Trinkoff et al., 2017). A third citation is for failing to post staffing levels and the resident census in a public place viewable by residents and their families. While purely an administrative failure, the citation may be emblematic of poor management and organization of staffing.

DiD specification. As in Section 5, we estimate the short-term and long-term effects of bankruptcy through a DiD regression. We use the same sample of matched stacked cohorts. However, we must modify our approach to account for the irregular timing of inspections: the time interval between standard inspections is 12 months on average, but the exact interval length varies substantially. To address this, we denominate time in *inspections relative to the bankruptcy filing*. Thus, letting τ index inspections, $\tau = -1$ corresponds to facility f's first standard inspection prior to the bankruptcy filing of the treated facility in match cohort $c(f)$. Likewise, $\tau = 1$ corresponds to the first standard inspection after the bankruptcy. Since complaint deficiencies are entirely sporadic, we attribute each post-bankruptcy complaint deficiency to the temporally closest post-bankruptcy standard inspection. Likewise, we attribute each pre-bankruptcy complaint deficiency to the temporally closest pre-bankruptcy standard inspection.

Other than this change in timing, our DiD specification is similar to equation (1) . We measure short-term effects based on relative performance changes in the first standard inspection after bankruptcy filing (i.e., $\tau = 1$), which typically occurs within one year after bankruptcy. For long-term effects, we examine performance changes after the first inspection (i.e., $\tau \geq 2$).[12] Formally, the DiD specification is:

$$y_{f,\tau} = \beta^S \cdot \mathbf{1}\{\tau = 1\} \cdot B_f + \beta^L \cdot \mathbf{1}\{\tau \geq 2\} \cdot B_f + \alpha_{\tau,c(f)} + \rho_{f,c(f)} + \epsilon_{f,\tau}. \tag{3}$$

As in equation (1), we include cohort-specific facility fixed effects $\rho_{f,c(f)}$ and cohort-by-inspection-time fixed effects $\alpha_{\tau,c(f)}$ to estimate a stacked DiD. The coefficients β^S and β^L respectively represent the short-term and long-term effects of bankruptcy. These effects are estimated by comparing changes in the outcome y over time for treated and control facilities.

Results. We estimate equation (3) and present the results in Table 6. Our first dependent variable is the total number of deficiencies in the τth standard inspection relative to

[12]Our findings are robust to excluding $\tau > 5$ to avoid implausibly long effect horizons.

Table 6: Performance on Health Inspections After Bankruptcy

	Standard Deficiencies	Complaint Deficiencies	Nursing Services Violations	Quality of Care Violations
$\tau = 1$	0.689*	0.365	0.078**	0.278*
	(0.371)	(0.333)	(0.035)	(0.166)
$\tau \geq 2$	0.047	0.160	-0.000	-0.007
	(0.493)	(0.273)	(0.032)	(0.124)
FE: Facility	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes
Observations	33,052	33,052	33,052	33,052
R^2	0.54	0.48	0.38	0.53
Mean	6.37	2.04	0.18	1.73
Std. Dev	5.19	3.70	0.49	1.92

Note. Each observation is a facility observed during the τth inspection relative to the bankruptcy filing date. Each column presents the results from estimating equation (3) using a different dependent variable. From left to right, the dependent variables are: the number of standard deficiencies, the number of complaint deficiencies, the number of deficiencies that fall under the "nursing services" category, and the number of deficiencies that fall under the "quality of care" category. Standard deficiencies are violations incurred during unannounced health inspector visits that occur on an annual basis. Complaint deficiencies are violations that arise from filed complaints. Standard errors are provided in parentheses and are clustered by nursing home chain. Event studies are provided in Figure E1. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

bankruptcy. We estimate equation (3) using this outcome and present the results in the first column of Table 6. We find that performance on these unannounced standard health inspections worsens immediately after a bankruptcy filing: bankrupt facilities are cited for 0.69 more deficiencies during their first standard inspection after the bankruptcy, relative to matched control facilities. This treatment effect is equal to 11% of the dependent-variable sample mean. For reference, this treatment effect is similar to the effect of increasing staff turnover from the 5th to 95th percentile, according to estimates from Shen, McGarry, and Gandhi (2023). Next, we define an analogous dependent variable measuring the total number of complaint deficiencies. We estimate equation (3) using this second dependent variable. The second column of Table 6 displays the results. While our point estimates suggest an increase in complaint deficiencies, the effect is statistically insignificant because of large standard errors.

Next, we define an outcome variable equal to the total number of standard-inspection deficiencies that specifically relate to nursing services (e.g., the citation for insufficient staffing discussed above). The third column of Table 6 presents the results from estimating equation (3) with this dependent variable. We find that a bankruptcy filing increases nursing services deficiencies by 0.078 in the short term (44% of the dependent-variable sample mean). In light of our results from Section 5 that bankruptcies increase turnover without impacting total staffing, this suggests that: (a) performance by new hires is comparatively worse than the staff they replaced or (b) retained staff perform worse. In Table E2, we show that post-bankruptcy nursing services deficiencies are concentrated in the three citations we discussed above: insufficient staffing, insufficient CNA training, and failure to post staffing levels.

Finally, we study the impact of bankruptcy filings on quality of care, using a dependent variable equal to the total number of "quality of care" deficiencies (e.g., the citation for excessive tube feeding described above). The fourth column of Table 6 shows the treatment effects from estimating equation (3) with this dependent variable. We find that a bankruptcy filing causes a short-term increase in quality of care deficiencies: citations rise by 0.28 (16% of the mean). In Table E3, we show that this increase is driven by the two citations emphasized earlier: excessive tube feeding and unnecessary use of bedrails. In Section 6.2, we show complementary results suggesting that staff use bedrails inappropriately to physically restrain residents against their will. In contrast to these significant effects, we find statistically insignificant effects for other quality of care deficiencies: failing to treat pressure ulcers, take steps to prevent accidents, and meet professional standards-of-practice.

Across all four of the dependent variables considered in Table 6, we find no statistically

significant evidence that bankruptcy has a long-term effect on inspections. This lack of significance might suggest that the harms of bankruptcy to patient health and safety are highly transitory. For example, facilities might take corrective actions after the first post-bankruptcy inspection that help the facility avoid repeat citations.

Finally, in Appendix E.2, we examine the severity and scope of the bankrupt facilities' additional deficiencies. Panel a of Table E1 shows that the deficiencies tend to be isolated incidents, consistent with new and inexperienced staff making mistakes, rather than widespread or systematic failures. Importantly, while additional deficiencies tend to be isolated, inspectors indicate that they could harm patients, rather than being purely procedural (panel b of Table E1).

6.2 Patient Health Outcomes

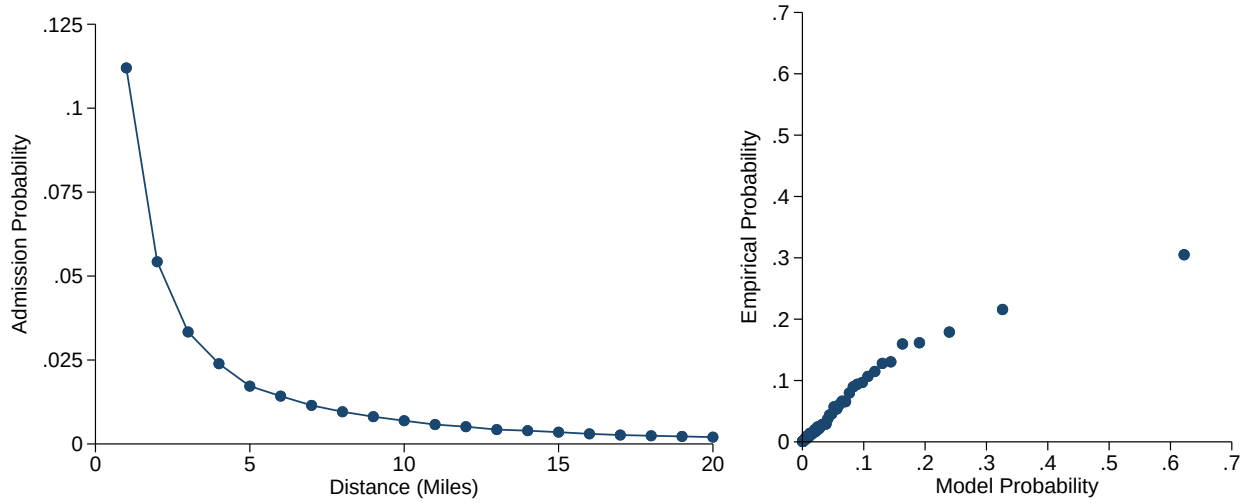
The previous sections show that bankruptcies result in greater staff turnover and poor performance on unannounced health inspections. While these results are concerning, they do not directly capture the effect of bankruptcies on patients' health. In this section, we show that bankruptcies worsen patient health outcomes. To measure these outcomes, we obtain patient-level Medicare claims data and resident assessment data from the Long Term Care Minimum Data Set (MDS). These data allow us to examine a variety of patient health outcomes, from hospitalizations to the level of independence in activities of daily living.

6.2.1 Instrumental-Variables Approach

Using patient health outcomes to evaluate a nursing home's quality of care is challenging because of an omitted-variables problem: outcomes are correlated with unobserved patient health characteristics that might vary systematically across facilities and time. Facility and time fixed effects solve this problem if the unobserved patient characteristics for each facility are constant across time. However, a bankruptcy filing could potentially change the composition of patients admitted to the bankrupt facility. This might occur because prospective patients avoid bankrupt facilities (Antill and Hunter, 2021) or because facilities adjust their admission or discharge policies after a bankruptcy filing (Gandhi, 2023; Hackmann, Pohl, and Ziebarth, 2024).

We address this concern with an instrumental-variables approach. Our instrument exploits quasi-random variation in a patient's physical proximity to a bankrupt facility. Our approach leverages the fact that patients are extremely sensitive to distance when choosing between nursing homes (Rahman et al., 2014; Hackmann, 2019; Gandhi, 2023; Einav, Finkelstein,

Figure 5: Relationship Between Distance and Probability of Admission



(a) Distance and Admission to Facility

(b) Model Probability of Admission to Bankrupt Facility

Note. For each patient i living in ZIP code $z(i)$, we assume that their facility choice set $F_{z(i)}$ contains all facilities within 50 miles of ZIP code $z(i)$. We construct a patient-facility-level dataset containing all patient-facility pairs (i, f) such that f is in i's choice set $F_{z(i)}$. We bin observations based on the distance $d(z(i), f)$ between the patient's ZIP code and the facility. In each bin, we calculate the fraction of pairs (i, f) such that patient i is admitted to facility f. In panel (a), we plot the rate of admissions (on the y axis) among all pairs (i, f) in the bin corresponding to the distance on the x axis. Then, using the same patient-facility dataset, we estimate equations (4)-(6) to calculate w_i, the model-implied probability that patient i is admitted to a bankrupt facility. In a patient-level dataset, we form bins based on w_i. In panel (b), we plot the share of patients admitted to a bankrupt facility (on the y axis) among all patients i in the bin corresponding to the value of w_i on the x axis.

and Mahoney, 2024). Figure 5 Panel (a) affirms this, showing that a patient is far more likely to choose a facility if it is close to their home. Formally, for each patient i living in ZIP code $z(i)$, we assume that their facility choice set $F_{z(i)}$ contains all facilities within 50 miles of ZIP code $z(i)$. We construct a patient-facility-level dataset containing all patient-facility pairs (i, f) such that f is in i's choice set $F_{z(i)}$. We bin observations based on the distance $d(z(i), f)$ between the patient's ZIP code and the facility. In each bin, we calculate the fraction of pairs (i, f) such that patient i is admitted to facility f. Figure 5 Panel (a) shows that this probability of patient i being admitted to facility f declines as the distance between the patient and the facility increases.

We use patients' preference for proximity to construct our instrument. One common approach to using spatial variation in proximity is the "differential distance" instrument,

which simply measures the patient's relative distance to the closest treated (bankrupt) and untreated (never bankrupt) facilities.[13] Intuitively, when treated facilities are relatively closer, individuals are more likely to be treated (i.e., receive care at a bankrupt facility). However, in considering only the closest treated and untreated facilities, this implementation ignores considerable variation attributable to other facilities. For example, being very close to many treated facilities might increase the probability of receiving care at a treated facility. To account for this possibility and more realistically model patients' facility choices, we use an alternative instrument construction. Specifically, our primary specification uses a distance-based discrete-choice model to calculate our instrument, as in Kessler and McClellan (2000); Geweke, Gowrisankaran, and Town (2003); Garthwaite, Ody, and Starc (2022); Cheng (2023); Olenski and Sacher (2024) and Einav, Finkelstein, and Mahoney (2024). We show in Appendix G.7 that our results generally hold (and are typically stronger) when we use the simpler differential-distance instrument.

We construct our instrument with a discrete-choice model. Formally, we assume that patient i receives utility u_{if} from choosing facility f. We parameterize u_{if} as:

$$u_{if} = \alpha_1 d(z(i), f) + \alpha_2 d(z(i), f)^2 + \epsilon_{if}, \tag{4}$$

where α_1, α_2 are parameters that we estimate, $z(i)$ is the patient's home ZIP code, $d(z(i), f)$ is the distance between ZIP code $z(i)$ and facility f, and ϵ_{if} is the patient's idiosyncratic utility, which we assume is Type-I Extreme Value distributed. This demand model implies the following probability that a resident i of ZIP code $z(i)$ receives care at facility f:

$$p_{z(i),f} = \frac{\exp\left(\alpha_1 d(z(i), f) + \alpha_2 d(z(i), f)^2\right)}{\sum_{f' \in F_{z(i)}} \exp\left(\alpha_1 d(z(i), f') + \alpha_2 d(z(i), f')^2\right)}, \tag{5}$$

where $F_{z(i)}$ is the choice set of facilities within 50 miles of $z(i)$.

We first estimate α_1 and α_2 via maximum likelihood using the same facility-patient dataset described above. We present the estimates from this standard estimation procedure in Table G1. Consistent with previous literature, our estimates imply that nursing home demand is highly elastic to distance: the average elasticity of $\hat{p}_{z(i),f}$ with respect to $d(z(i), f)$ is -2.5.

Importantly, for each ZIP code z and each facility $f \in F_z$, our estimates of α_1, α_2 imply

[13] For examples of this approach, see Grabowski et al. (2013); Rahman, Norton, and Grabowski (2016); Huang and Bowblis (2019); Li, Liu, and Taylor (2023); Gupta et al. (2024); Antill and Bellon (2024).

a predicted probability $\hat{p}_{z,f}$ that patients in ZIP code z choose facility f. We aggregate this across bankrupt facilities to construct our instrument. Formally, our instrument is the model-implied probability w_i that a patient i receives care at a recently-bankrupt facility:

$$w_i = \sum_{f \in F_{z(i)}} \hat{p}_{z(i),f} B_{f,t(i)}, \tag{6}$$

where $t(i)$ is the week of patient i's admission and $B_{f,t(i)}$ is an indicator for facility f having filed for bankruptcy within 3 years prior to $t(i)$.[14] w_i is constructed using only distances between patients and nearby nursing homes. Intuitively, it is the probability that a patient chooses a bankrupt facility given their ZIP code and the model-implied patient aversion to distant facilities.

Figure 5 Panel (b) shows that our instrument w_i closely tracks the realized probability that a patient is admitted to a bankrupt facility. Formally, we use equations (4)-(6) to calculate w_i for each patient i in a patient-level dataset. We form bins based on w_i. In Figure 5 Panel (b), we plot the share of patients admitted to a bankrupt facility (on the y axis) among all patients i in the bin corresponding to the value of w_i on the x axis. Our model-predicted probabilities tightly mirror the corresponding empirical probabilities. This suggests that our instrument is likely to satisfy the relevance and monotonicity assumptions required for a valid instrument (Imbens and Angrist, 1994).

We use our instrument to estimate the effect of receiving care at a bankrupt facility. Formally, we estimate the following system by two-stage least squares (2SLS):

$$B_{f(i),t(i)} = \gamma w_i + \rho^B_{f(i)} + \eta^B_{z(i)} + \alpha^B_{t(i)} + X_i \varphi^B + \nu_i, \tag{7}$$

$$Y_i = \beta \widehat{B}_{f(i),t(i)} + \rho_{f(i)} + \eta_{z(i)} + \alpha_{t(i)} + X_i \varphi + \epsilon_i, \tag{8}$$

where Y_i is a health outcome (e.g., hospitalization) and the terms ρ, η, and α represent facility, ZIP code, and calendar-year-week fixed effects, respectively. In equation (8), $\widehat{B}_{f(i),t(i)}$ is the instrumented value of $B_{f(i),t(i)}$ calculated in the first stage. Finally, X_i contains a host of other health and demographic controls, including: (i) the patient's age, race, and gender, captured by a series of indicator variables, (ii) an indicator variable for the patient having end-stage renal disease, (iii) 22 indicator variables for other distinct chronic conditions, (iv) an indicator for the patient's "dual eligibility" for both Medicaid and Medicare, and (v) a

[14] Table G3 and Table G4 show similar results if we study bankruptcies one or five years prior to $t(i)$.

fixed effect for the patient's primary diagnosis from their pre-admission hospital stay.[15] Since many of our measures are only observed for enrollees in traditional fee-for-service Medicare, we follow Gupta et al. (2024) and Einav, Finkelstein, and Mahoney (2024) in restricting our sample to these enrollees. We cluster standard errors at the ZIP code level.

Consistent with Figure 5, our instrument w_i is strongly correlated with the endogenous variable $B_{f(i),t(i)}$. When we estimate (7), the F-statistic for the instrument is 1,736, implying that a weak-instrument problem is unlikely. The instrument is therefore valid as long as it satisfies the exclusion restriction: conditional on controls, the instrument w_i must be uncorrelated with the error term ϵ_i (Abadie, 2003). Note that since $\hat{p}_{z(i),f}$ depends only on the patient's relative distances to nearby facilities, w_i also varies only with the relative distances of nearby bankrupt and non-bankrupt facilities. Our exclusion-restriction assumption can thus be stated as follows: after conditioning on our host of fixed effects and patient controls, the relative geographic proximity of bankrupt and non-bankrupt facilities does not correlate with health outcomes except through choice of facility. While the assumption is fundamentally untestable, we provide some evidence supporting the assumption in Figure G1. Specifically, in this figure, we show that the instrument has little correlation with observable patient characteristics that are likely to influence or predict health outcomes.

Our fixed effects and controls play a key role in the plausibility of our exclusion-restriction assumption. Facility fixed effects ensure that systematic differences in quality of care across nursing homes do not influence our estimate of β (equation 8). Likewise, our time fixed effects adjust for secular trends. Controlling for patient health and demographic characteristics adjusts for patient observables that predict health outcomes.

Finally, ZIP code fixed effects control for systematic spatial differences in patient health. Absent geographic controls, one might be concerned that bankrupt facilities are located in areas near patients who are sicker in ways that are not fully captured by our controls. Since the distance from a patient's ZIP code to a given facility never changes, ZIP code fixed effects help exclude systematic spatial variation in health. However, the set of facilities that have recently filed for bankruptcy *does* change over time. When a facility files for bankruptcy, patients in nearby ZIP codes suddenly become closer to a bankrupt facility. Because patients tend to prefer close facilities, patients from those ZIP codes become more likely to receive care at a bankrupt facility. Moreover, the corresponding changes in the probability of receiving care at a bankrupt facility will tend to be largest for ZIP codes that are the most relatively

[15] In order for a nursing home patient to qualify for Medicare reimbursement, they are typically required to have had a hospital stay of at least three days and concluded within the 30 days prior to nursing home admission. This stay is known as a "qualifying stay."

proximate to the filing facility. In this sense, our key identifying variation has two sources: across-time changes in the set of facilities that are bankrupt and geographic variation in which ZIP codes are relatively closer to the newly bankrupt facilities.

6.2.2 Results

We estimate equation (8) for several health outcomes Y_i. In Table 7, we present the estimate β for each health outcome. These estimates capture the effect of a facility's bankruptcy filing on patients' health.

Claims-based outcomes. We first examine health outcomes constructed using Medicare claims and enrollment records. In Table 7 Panel (A), each column corresponds to one of these outcomes. To begin, we examine patient mortality, captured by an indicator equal to one if a patient dies within 90 days of admission to the facility. In the first column, we show with a high degree of precision that admission to a recently-bankrupt facility does not increase the likelihood of mortality.

Next, we examine hospitalization, captured by an indicator equal to one if a patient is hospitalized within 90 days of admission. In the second column of Table 7 Panel (A), we show that a facility's bankruptcy increases the probability a patient is hospitalized by 1.44 percentage points (4.1% of the dependent-variable sample mean). This increase in hospitalizations is a serious concern: a principal goal of nursing home care is to prevent the need for hospitalization. Accordingly, CMS pays close attention to the rate at which nursing home patients are hospitalized when measuring a facility's quality.

It is important to emphasize that these bankruptcy-induced hospitalizations represent major medical harms to patients: a patient's health must have substantially declined for hospital staff to admit them as an inpatient. In fact, these bankruptcy-induced hospitalizations appear to be more serious than typical hospitalizations. To show this, we define an outcome variable equal to the number of days that a patient spends in the hospital within 90 days of being admitted to the nursing home facility. The third column of Table 7 Panel (A) shows that a bankruptcy increases the number of days that the patient spends at the hospital by 0.29 days (7.9% of the sample mean). Comparing the second and third columns, a bankruptcy increases the hospitalization rate by 4.1% of the sample mean, yet it disproportionately increases the number of hospital days by 7.9% of the sample mean. In this sense, bankruptcy-induced inpatient hospitalizations tend to be particularly severe.

Table 7: Health Impacts of Provider Bankruptcy

Panel A: Claims-based Outcomes

	Mortality	Hospitalization	Hospital Days	Fall-Based Hospitalization	Emergency Department
Bankrupt	-0.0021	0.0144**	0.2904***	0.0013	0.0091
	(0.0044)	(0.0058)	(0.1057)	(0.0024)	(0.0064)
N	9,853,046	9,853,046	9,853,046	9,853,046	9,853,046
R^2	0.079	0.103	0.086	0.024	0.099
Mean	0.151	0.347	3.68	0.034	0.433
SD	0.358	0.476	8.83	0.18	0.496

Panel B: Assessment-based Outcomes

	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
Bankrupt	0.0153***	-0.0024	0.0200***	0.0058	-0.5251***
	(0.0037)	(0.0067)	(0.0071)	(0.0054)	(0.1093)
N	2,907,000	2,907,663	2,906,850	2,907,473	2,907,416
R^2	0.250	0.194	0.086	0.099	0.203
Mean	0.020	0.139	0.143	0.080	7.72
SD	0.139	0.346	0.35	0.272	4.12

Note. Using 2SLS regressions (equation (8)) in a patient-level dataset, we estimate the effect of receiving care at a recently-bankrupt facility on patient health outcomes. We instrument for visiting a recently-bankrupt facility (one that filed within three years of the patient's admission) using w_i, a patient's model-implied likelihood of visiting a bankrupt facility given the patient's home ZIP code (equation (6)). In panel A, each column corresponds to a health outcome constructed using Medicare claims and enrollment records. These outcomes include indicators for a patient's mortality, hospitalization, fall-based hospitalization, and emergency-department visit within 90 days of the patient's admission to the facility. We also include the number of days the patients spends in the hospital within 90 days of admission to the facility. In panel B, each outcome is measured on a patient assessment conducted 30 days after admission to a facility. Four of the outcomes are indicators for: (i) the use of physical restraints, (ii) the use of chemical restraints, (iii) the patient suffering pressure ulcers (bed sores), or (iv) the use of a catheter. The final outcome is the patient's "Activities of Daily Living" (ADL) score. We cluster standard errors at the level of a patient's home ZIP code . We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. In the appendix, we show corresponding results for: (i) different definitions of a recently-bankrupt facility (the facility filed for bankruptcy in the last year in Table G3 and the facility filed for bankruptcy in the last five years in Table G4), (ii) different assessment time horizons (5-day, 14-day, 60-day, and 90-day assessments in Table G2), (iii) additional health outcomes (Table G5), and (iv) assuming preferences in log-distance (Table G6).

We are unable to identify the precise cause of the additional bankruptcy-induced hospitalizations. In the fourth column of Table 7 Panel (A), we show that additional hospitalizations are not due to patients falling. However, nursing home patients can be hospitalized for many other reasons, such as infections or complications from comorbidities such as diabetes or chronic obstructive pulmonary disease (COPD). While we cannot pinpoint the reason for hospitalization, the point estimate in the final column of Table 7 Panel (A) suggests that some bankruptcy-induced hospitalizations may start with an emergency-department visit. However, this point estimate is imprecisely measured and it is therefore statistically indistinguishable from zero.

Adverse outcomes, such as hospitalizations, might be more likely when staff are less familiar with a facility and its residents. We explore this possibility in Section 7 using a randomized survey experiment of nursing staff with experience working at nursing home facilities.

Assessment-based outcomes. We have shown that bankruptcies and the resultant turnover in staff lead to patient hospitalization, a particularly severe adverse outcome. We now study whether bankruptcies harm patients in other ways that do not result in hospitalization or additional claims. Specifically, we leverage detailed MDS resident assessments to quantify changes in quality of care.

To ensure that we only compare patients who have been at a facility for the same length of time, we restrict our analysis to Medicare-mandated assessments conducted around the 30th day of a resident's stay. Medicare requires these high-frequency MDS assessments early in a resident's stay as part of the "Prospective Payment System" (PPS).[16]

We estimate equation (8) using outcomes Y_i that are measured on these 30-day assessments. Our estimates, which we display in Table 7 Panel (B), indicate meaningful degradations in care after bankruptcy. First, recently-bankrupt nursing homes appear substantially more likely to physically restrain patients.[17] The first column of Panel (B) shows that a bankruptcy increases the probability that a patient will be physically restrained by 1.5 per-

[16]Focusing on these assessments necessarily excludes parts of stays not covered by Medicare. In particular, for long stay patients, we would include outcomes recorded as part of any initial Medicare-reimbursed care but would not include quarterly and annual assessments taken after transitioning from Medicare coverage to Medicaid or private pay.

[17]We do not observe similar increases in "chemical restraints" — the inappropriate use of drugs such as antipsychotics to sedate patients. We include all antipsychotic use and schizophrenia diagnoses as indicators of chemical restraint because nursing homes have been shown to frequently improperly diagnose schizophrenia to justify the use of antipsychotics (Thomas, Gebeloff, and Silver-Greenberg, 2021).

centage points, a shocking 77% of the sample mean. It is important to emphasize that this increased use of physical restraints—such as using ties, belts, straps, rails, or other equipment to limit residents' movement or access to their own body—is alarming. A primary objective in long-term care is to respect residents' bodily autonomy, as well as to encourage them to participate in activities of daily living. Many patient advocates, clinicians, and researchers argue that such restraints are a form of abuse (Lindbloom et al., 2007; Tolson and Morley, 2012), as they are rarely in the interest of the patient and are primarily used for the convenience of inexperienced, incompetent, or overburdened staff. CMS shares this view and penalizes the use of restraints in their quality rating system for nursing homes.

Next, we show that bankruptcies increase the rate of pressure ulcers, known colloquially as "bedsores." In the third column of panel (B), we show that a bankruptcy increases the probability of a pressure ulcer by two percentage points (14% of the sample mean). Pressure ulcers typically arise from uninterrupted pressure preventing blood flow. Many patients in the nursing home setting might be bedridden or substantially immobile and are prone to developing pressure ulcers if they are not repositioned or transferred with sufficient frequency. Pressure ulcers are substantially preventable, but doing so requires considerable effort from staff. For example, long-standing clinical guidelines recommend assessment and careful repositioning—which often requires multiple staff—every two hours (Smith, 1995; Reddy, Gill, and Rochon, 2006). The presence of pressure ulcers suggests that a resident is not receiving sufficient care to prevent their development. As such, the CMS quality rating system for nursing homes penalizes facilities for pressure ulcers.

Our point estimates also suggest, albeit imprecisely, that bankrupt facilities might use catheters more frequently. The use of catheters, except when medically necessary, is generally discouraged. However, a facility might impose an unnecessary catheter on a resident to avoid the considerable staff assistance that the resident would otherwise require for toileting. The CMS quality rating system penalizes the use of catheters to disincentivize facilities from using medically unnecessary catheterization to reduce demands on staff to assist with toileting.

We also examine how bankruptcy affects the extent of assistance that residents receive with their activities of daily living (ADLs). These activities include moving, bathing, feeding, and toileting. The fifth column of panel (B) shows that residents of a recently-bankrupt facility receive markedly less assistance with their ADLs. This must be interpreted carefully. Often, a low level of assistance with ADLs is considered a positive indicator of quality: it could be that the facility provided effective care that increased residents' capacity for independence. However, low assistance with ADLs is concerning if residents require assistance but do not

receive it: this prevents residents from fully engaging in their ADLs. Here, the latter seems more likely given the other evidence of worsening care that we observe. Moreover, we find in Appendix G.3 that bankruptcy reduces assistance with ADLs even in residents' earliest assessments. Given that nursing home care is unlikely to improve a patient's capacity for independence within a few days, the estimates are most plausibly interpreted as recently-bankrupt facilities providing insufficient assistance with ADLs.

Finally, it is important to note that nursing home care is both clinical and *residential*. Patients reside at the facility and spend only a fraction of their time receiving clinical care. Outside of that care, residents live their lives at the facility, participating in activities and developing relationships with other residents and staff. While our empirical analysis emphasizes clinical outcomes, as they tend to be measured by claims and assessments, the broader residential experience is just as important. There may be important non-clinical ways in which bankruptcy and turnover degrades residents' experience (e.g., turnover removes the staff most familiar with the residents). While we are unable to quantify these impacts, this is an important consideration for policymakers, patient advocates, and economists.

Robustness. Appendix G presents various robustness checks and extensions. In Section G.3, we repeat our analysis separately for 5-day, 14-day, 60-day, and 90-day assessments. Likewise, in Section G.4, we repeat our analysis defining recent bankruptcies as those that occurred within the previous year or the previous five years. Then, in Section G.5, we examine other outcomes, such as weight changes and antidepressant use. Finally, in Sections G.6 and G.7, respectively, we repeat our analysis assuming preferences in log-distance and using a simple differential-distance instrument.

7 Experimental Evidence on Mechanisms

We have shown that a nursing home bankruptcy filing causes nurse turnover (Section 5) and a decline in patient health (Section 6). These results raise several questions: do nurses quit in reaction to a bankruptcy filing, or are they fired as part of the firm's bankruptcy strategy? Is nurse turnover the mechanism driving the decline in patient health, or do bankruptcy filings coincide with some other shift in strategy that harms patients?

To answer these questions, we conduct an online survey experiment. We ran an our survey over the period from November 2022 to December 2022 using a platform called Lucid. We survey 247 nurses, all of whom have experience working in nursing homes. The survey has

two parts. First, each participant reads descriptions of hypothetical patient-care scenarios (e.g., a nurse gives a patient medicine). Participants estimate each hypothetical patient's risk of a negative outcome. We randomly vary the tenure of the nurse in each hypothetical scenario, holding every other detail fixed. According to our randomized design, participants believe that a reduction in nurse tenure causally increases negative-outcome risk by 44%. In this sense, according to nursing home workers, nurse turnover causes a decline in patient health. Second, each participant reads a description of a hypothetical nursing facility. Each participant estimates the rate of voluntary departures at the facility. We randomly vary the bankruptcy status of the facility, holding all other details fixed. Our randomized design shows that a bankruptcy causally increases voluntary nurse departures by 47%.

Together, the survey experiment results reveal that: (i) nurses are likely to quit in response to a bankruptcy filing, and (ii) the nurse turnover caused by a bankruptcy filing is likely to harm patients. An important caveat is that our nurse participants evaluate hypothetical scenarios in an unincentivized manner. Nonetheless, we show that our preferred interpretation of our main results is consistent with the collective experience of 247 nursing home workers. In the following sections, we briefly summarize the experiment and its implications. In Appendix A, we provide a detailed description of the survey experiment.

7.1 Nurses Voluntarily Quit in Response to a Bankruptcy Filing

At the start of our survey, each nurse participant describes their prior work experience. We confirm that each nurse has experience working at a nursing home. Using standard attention tests, we also confirm that each nurse is carefully reading the survey questions.

In the second part of our survey, each nurse reads a description of a job at a hypothetical nursing home. Each participant's hypothetical job description is designed to match their own prior work experience: the wage, nursing role, and location match the participant's description of their most recent job. We ask each participant to imagine they currently have this hypothetical job and to estimate: (i) how likely they would be to search for a job at another facility, and (ii) what fraction of nurses at this hypothetical facility would voluntarily quit in the next year.

We randomly assign each nurse participant to one of three groups. In the control group, the hypothetical facility in the description can afford to pay its expenses. In the "Distressed" group, the facility has a 25% chance of filing for Chapter 11 bankruptcy in the next year. In the "Bankrupt" group, participants read the following: "While [the facility] is currently open, it recently filed for Chapter 11 bankruptcy and is currently in bankruptcy proceedings."

We compare participant responses across randomly assigned groups, controlling for observable participant characteristics with OLS regressions. Relative to control-group participants, participants in the Bankrupt group: (i) are 28.8 percentage points more likely to search for a new job (75% of the control-group mean), and (ii) estimate a rate of voluntary attrition that is 18 percentage points higher (47% of the control-group mean). These treatment effects are economically and statistically significant ($p < 0.01$). We similarly find significant treatment effects associated with the Distressed treatment, though these are smaller in magnitude. We provide further details and results in Appendix A.

7.2 Nurse Turnover Harms Patients and Reduces Efficiency

At the start of the survey, each participant reports the nursing role corresponding to their work experience: LPN, CNA, or RN. The participant then reads hypothetical patient-care scenarios involving tasks corresponding to that role. We worked with a nurse to design realistic task descriptions for each nursing role.

After reading each hypothetical scenario, each participant reports: (i) the likelihood that the hypothetical nurse makes a mistake, leading to a bad outcome for the hypothetical patient (e.g., administering an incorrect medication dose); and (ii) the amount of time that the hypothetical nurse would need to complete the task.

We randomly assign each survey participant to one of two groups. In the control group, the hypothetical nurse performing the task in each hypothetical scenario has one year of tenure (i.e., the nurse has worked at the hypothetical facility for one year). In the treatment group, the hypothetical nurse has one week of tenure. All other details in the hypothetical scenarios are identical across groups.

Once again, we compare participant responses across randomly assigned groups. Relative to the control-group participants, participants in the treatment group (one week of tenure) report: (i) a 9.7 percentage point increase in the rate of nurse mistakes (44% of the control-group mean), and (ii) a 6 minute higher completion time (14% of the control-group mean). Both effects are statistically significant ($p < 0.01$).[18]

[18] We cluster standard errors by participant to adjust for the fact that each participant evaluates multiple scenarios.

7.3 Discussion

Together, the results from the randomized experiment allow for a back-of-the-envelope calculation to estimate the effect of bankruptcy on patient outcomes through the loss of experienced nursing workers. We find that bankruptcy increases voluntary attrition by 47% of the control-group mean, while turnover increases the reported rate of bad patient outcomes (nurse mistakes) by roughly 44%. Therefore, a crude back-of-the-envelope calculation shows that bankruptcy is likely to increase adverse patient outcomes by $44\% \times 47\% = 21\%$ through the loss of experienced employees. Analogously, a bankruptcy reduces nurse efficiency (timely task completion) by $14\% \times 47\% = 7\%$ through a loss of facility-specific human capital.

These results are based on nurses evaluating hypothetical scenarios in an unincentivized manner. Nonetheless, these nurses are likely to report answers consistent with their experience because (i) they have no incentive to lie and (ii) our across-participant design mitigates experimenter-demand concerns since participants are unaware of the treatment.[19]

8 Conclusion

This paper leverages administrative and survey data from the healthcare sector to study the implication of healthcare provider bankruptcies in the US nursing home industry. Using a DiD design, we show that a Chapter 11 bankruptcy filing immediately increases worker turnover at the bankrupt facility. This increase in turnover coincides with an increase in failed facility health inspections. Next, we use patient-level health outcome data to study rehospitalizations. Using an instrumental variables approach, we show that a patient is 1.44 percentage points more likely to be forced to return to the hospital if she visits a bankrupt facility, relative to the counterfactual in which the same patient visits the same facility prior to its bankruptcy filing. Finally, using an online survey experiment, we confirm our preferred interpretation: bankruptcy filings lead to voluntary worker departures that harm patients.

[19] I.e., treatment-group participants do not know how their descriptions differ from those viewed by control-group participants.

References

Abadie, A. 2003. Semiparametric instrumental variable estimation of treatment response models. *Journal of econometrics* 113:231–63.

Abadie, A., S. Athey, G. W. Imbens, and J. M. Wooldridge. 2023. When should you adjust standard errors for clustering? *The Quarterly Journal of Economics* 138:1–35.

Adelino, M., K. Lewellen, and W. B. McCartney. 2022. Hospital financial health and clinical choices: Evidence from the financial crisis. *Management Science* 68:2098–119.

Adelino, M., K. Lewellen, and A. Sundaram. 2015. Investment decisions of nonprofit firms: Evidence from hospitals. *The Journal of Finance* 70:1583–628.

Agha, L., K. M. Ericson, K. H. Geissler, and J. B. Rebitzer. 2022. Team relationships and performance: Evidence from healthcare referral networks. *Management science* 68:3735–54.

Agha, L., B. Frandsen, and J. B. Rebitzer. 2019. Fragmented division of labor and healthcare costs: Evidence from moves across regions. *Journal of Public Economics* 169:144–59.

Aghamolla, C., P. Karaca-Mandic, X. Li, and R. T. Thakor. 2024. Merchants of death: The effect of credit supply shocks on hospital outcomes. *American Economic Review* 114:3623–68.

Antill, S. 2022. Do the right firms survive bankruptcy? *Journal of Financial Economics* 144:523–46.

———. 2024. Are bankruptcy professional fees excessively high? *The Review of Financial Studies* 37:3595–647.

Antill, S., and A. Bellon. 2024. The real effects of bankruptcy forum shopping. Working Paper, Harvard Business School.

Antill, S., and S. R. Grenadier. 2019. Optimal capital structure and bankruptcy choice: Dynamic bargaining versus liquidation. *Journal of Financial Economics* 133:198–224.

Antill, S., and M. Hunter. 2021. Consumer choice and corporate bankruptcy. Working Paper, Harvard Business School.

Antill, S., N. Wang, and Z. Jiang. 2024. Creditor-on-creditor violence and secured debt dynamics. Working Paper, Harvard Business School.

Antwi, Y. A., and J. R. Bowblis. 2018. The impact of nurse turnover on quality of care and mortality in nursing homes: Evidence from the great recession. *American Journal of Health Economics* 4:131–63.

Araujo, A., R. Ferreira, S. Lagaras, F. Moraes, J. Ponticelli, and M. Tsoutsoura. 2023. The labor effects of judicial bias in bankruptcy. *Journal of Financial Economics* 150:103720–.

Baghai, R. P., R. C. Silva, V. Thell, and V. Vig. 2021. Talent in distressed firms: Investigating the labor costs of financial distress. *The Journal of Finance* 76:2907–61.

Balasubramanian, S. 2023. Healthcare sector bankruptcies are on the rise. *Forbes.* https://www.forbes.com/sites/saibala/2023/08/27/healthcare-sector-bankruptcies-are-on-the-rise/.

Berk, J. B., R. Stanton, and J. Zechner. 2010. Human capital, bankruptcy, and capital structure. *The Journal of Finance* 65:891–926.

Borders, S., and S. M. Blank. 2021. 1-Day Prepackaged Bankruptcy. *Bloomberg Law* Contributed by King & Spalding LLP attorneys.

Brown, J., and D. A. Matsa. 2016. Boarding a sinking ship? An investigation of job applications to distressed firms. *The Journal of Finance* 71:507–50.

Carter, M., and C. Phillips. 1988. Staff turnover as an indicator of quality of care in Australian nursing homes. *Proceedings of the Annual Conference of the Australian Association of Gerontology* 23:100–.

Castle, N. G., J. Engberg, and A. Men. 2007. Nursing Home Staff Turnover: Impact on Nursing Home Compare Quality Measures. *The Gerontologist* 47:650–61.

Cengiz, D., A. Dube, A. Lindner, and B. Zipperer. 2019. The effect of minimum wages on low-wage jobs. *The Quarterly Journal of Economics* 134:1405–54.

Centers for Medicare & Medicaid Services. 2019. CMS Improving Nursing Home Compare in April 2019.

Centers for Medicare & Medicaid Services. 2021. List of revised ftags. https://www.cms.gov/Medicare/Provider-Enrollment-and-Certification/GuidanceforLawsAndRegulations/Downloads/List-of-Revised-FTags.pdf.

———. 2025. National health expenditure data - historical. https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/historical.

Centers for Medicare and Medicaid Services. 2023. State operations manual, chapter 7: Survey and enforcement process for skilled nursing facilities and nursing facilities. Revision 213, 02-10-23.

———. 2025. Design for care compare nursing home five-star quality rating system: Technical users' guide. Technical guide, Centers for Medicare and Medicaid Services. Version: January 2025.

Cheng, A. 2023. Demand for quality in the presence of information frictions: Evidence from the nursing home market. Working Paper, Massachusetts Institute of Technology.

Clarke, S. P., and N. E. Donaldson. 2008. Nurse staffing and patient care quality and safety. In *Patient Safety and Quality: An Evidence-Based Handbook for Nurses*, Advances in Patient Safety, chap. 25. Rockville (MD): Agency for Healthcare Research and Quality (US).

Donaldson, J. R., E. R. Morrison, G. Piacentino, and X. Yu. 2020. Restructuring vs. bankruptcy. Working Paper, University of Southern California.

Einav, L., A. Finkelstein, and N. Mahoney. 2024. Producing health: measuring value added of nursing homes. Working Paper, National Bureau of Economic Research.

Ellias, J. 2022. Employee bankruptcy trauma. Working Paper, Harvard Law School.

Falato, A., and N. Liang. 2016. Do creditor rights increase employment risk? Evidence from loan covenants. *The Journal of Finance* 71:2545–90.

Friedrich, B. U., and M. B. Hackmann. 2021. The returns to nursing: Evidence from a parental-leave program. *The Review of Economic Studies* 88:2308–43.

Gandhi, A. 2023. Picking your patients: Selective admissions in the nursing home industry. Working Paper, UCLA Anderson.

Gandhi, A., I. Larkin, B. McGarry, K. Wen, H. Yu, S. Berry, V. Mor, M. Syme, and E. White. 2024a. The health and employment effects of employer vaccination mandates. Working Paper, NBER Working Paper.

Gandhi, A., and A. Olenski. 2024. Tunneling and hidden profits in health care. Working Paper 32258, National Bureau of Economic Research. Revised September 2024.

Gandhi, A., K. Ruffini, A. Olenski, and K. Shen. 2024b. Alleviating worker shortages through targeted subsidies: Evidence from incentive payments in healthcare. Working Paper, UCLA Anderson.

Gandhi, A., Y. Song, and P. Upadrashta. 2020. Have private equity owned nursing homes fared worse under covid-19? Working paper, UCLA Anderson.

———. 2022. Private equity, consumers, and competition. Working paper, UCLA Anderson.

Gandhi, A., H. Yu, and D. C. Grabowski. 2021. High nursing staff turnover in nursing homes offers important quality information. *Health Affairs* 40:384–91.

Garthwaite, C., C. Ody, and A. Starc. 2022. Endogenous quality investments in the U.S. hospital market. *Journal of Health Economics* 84:102636–. ISSN 0167-6296.

Geweke, J., G. Gowrisankaran, and R. J. Town. 2003. Bayesian inference for hospital quality in a selection model. *Econometrica* 71:1215–38.

Goodman-Bacon, A. 2021. Difference-in-differences with variation in treatment timing. *Journal of econometrics* 225:254–77.

Gortmaker, J., J. Jeffers, and M. Lee. 2022. Labor reactions to credit deterioration: Evidence from linkedin activity. Working Paper, HEC Paris.

Grabowski, D. C., Z. Feng, R. Hirth, M. Rahman, and V. Mor. 2013. Effect of nursing home ownership on the quality of post-acute care: An instrumental variables approach. *Journal of health economics* 32:12–21.

Graham, J. R., H. Kim, S. Li, and J. Qiu. 2023. Employee costs of corporate bankruptcy. *The Journal of Finance* 78:2087–137.

Griffin, J. M., and A. Priest. 2025. Overbilling and killing? An examination of the skilled nursing industry. Working Paper, University of Texas Austin.

Gross, T., R. Kluender, F. Liu, M. J. Notowidigdo, and J. Wang. 2021. The economic consequences of bankruptcy reform. *American Economic Review* 111:2309–41–. doi:10.1257/aer.20191311.

Gupta, A., S. T. Howell, C. Yannelis, and A. Gupta. 2024. Owner incentives and performance in healthcare: Private equity investment in nursing homes. *The Review of Financial Studies* 37.

Hackmann, M. B. 2019. Incentivizing better quality of care: The role of medicaid and competition in the nursing home industry. *American Economic Review* 109:1684–716.

Hackmann, M. B., R. V. Pohl, and N. R. Ziebarth. 2024. Patient versus provider incentives in long-term care. *American Economic Journal: Applied Economics* 16:178–218.

Harrington, C., J. F. Schnelle, M. McGregor, and S. F. Simmons. 2016. The need for higher minimum staffing standards in U.S. nursing homes. *Health Services Insights* 9:13–9. ISSN 1178-6329. doi:10.4137/hsi.s38994.

Hortaçsu, A., G. Matvos, C. Shin, C. Syverson, and S. Venkataraman. 2011. Is an automaker's road to bankruptcy paved with customers' beliefs? *American Economic Review* 101:93–7.

Hortaçsu, A., G. Matvos, C. Syverson, and S. Venkataraman. 2013. Indirect costs of financial distress in durable goods industries: The case of auto manufacturers. *The Review of Financial Studies* 26:1248–90.

Huang, S. S., and J. R. Bowblis. 2019. Private equity ownership and nursing home quality: An instrumental variables approach. *International journal of health economics and management* 19:273–99.

Imbens, G. W., and J. D. Angrist. 1994. Identification and estimation of local average treatment effects. *Econometrica* 62:467–75.

Jensen, M. C. 1986. Agency costs of free cash flow, corporate finance, and takeovers. *The American economic review* 76:323–9.

Kessler, D. P., and M. B. McClellan. 2000. Is hospital competition socially wasteful? *The Quarterly Journal of Economics* 115:577–615. ISSN 00335533, 15314650.

Landi, H. 2022. Healthcare companies' default risk steadily rising, most owned by private equity: Moody's. *Fierce Healthcare*. https://www.fiercehealthcare.com/finance/healthcare-companies-default-risk-steadily-rising-most-owned-private-equity-moodys.

Li, X., T. Liu, and L. A. Taylor. 2023. Common ownership and innovation efficiency. *Journal of financial economics* 147:475–97.

Lin, H. 2014. Revisiting the relationship between nurse staffing and quality of care in nursing homes: An instrumental variables approach. *Journal of Health Economics* 37:13–24. ISSN 18791646.

Lindbloom, E. J., J. Brandt, L. D. Hough, and S. E. Meadows. 2007. Elder mistreatment in the nursing home: A systematic review. *Journal of the American Medical Directors Association* 8:610–6. doi:10.1016/j.jamda.2007.09.001.

Liu, T. 2021. Bargaining with private equity: Implications for hospital prices and patient welfare. Working Paper, MIT Sloan.

Loomer, L., D. C. Grabowski, H. Yu, and A. Gandhi. 2021. Association between nursing home staff turnover and infection control citations. *Health Services Research* n/a.

Matsa, D. A. 2011. Running on empty? Financial leverage and product quality in the supermarket industry. *American Economic Journal: Microeconomics* 3:137–73.

Mitchell, S. L., J. L. Buchanan, S. Littlehale, and M. B. Hamel. 2004. Tube-feeding versus hand-feeding nursing home residents with advanced dementia: A cost comparison. *Journal of the American Medical Directors Association* 5:S23–9.

Mitchell, S. L., V. Mor, P. L. Gozalo, J. L. Servadio, and J. M. Teno. 2016. Tube feeding in U.S. nursing home residents with advanced dementia, 2000-2014. *Jama* 316:769–70.

Mukamel, D. B., D. Saliba, H. Ladd, and R. T. Konetzka. 2023. Dementia care is widespread in us nursing homes; facilities with the most dementia patients may offer better care. *Health Affairs* 42:795–803.

Nyweide, D. J., D. L. Anthony, J. P. W. Bynum, R. L. Strawderman, W. B. Weeks, L. P. Casalino, and E. S. Fisher. 2013. Continuity of care and the risk of preventable hospitalization in older adults. *JAMA Internal Medicine* 173:1879–85.

of Inspector General, O. 2014. Adverse events in skilled nursing facilities: National incidence among medicare beneficiaries. Working Paper, Department of Health and Human Services.

Olenski, A. 2023. Reallocation and the (in)efficiency of exit in the U.S. nursing home industry. *working paper* .

Olenski, A., and S. Sacher. 2024. Estimating nursing home quality with selection. *Review of Economics and Statistics* 1–31.

Phillips, G., and G. Sertsios. 2013. How do firm financial conditions affect product quality and pricing? *Management Science* 59:1764–82. ISSN 00251909. doi:10.1287/mnsc.1120.1693.

Rahman, M., D. C. Grabowski, P. L. Gozalo, K. S. Thomas, and V. Mor. 2014. Are dual eligibles admitted to poorer quality skilled nursing facilities? *Health Services Research* 49:798–817. doi:https://doi.org/10.1111/1475-6773.12142.

Rahman, M., E. C. Norton, and D. C. Grabowski. 2016. Do hospital-owned skilled nursing facilities provide better post-acute care quality? *Journal of Health Economics* 50:36–46.

Reddy, M., S. S. Gill, and P. A. Rochon. 2006. Preventing pressure ulcers: A systematic review. *JAMA* 296:974–84. doi:10.1001/jama.296.8.974.

Roberts, T., K. Nolet, and B. Bowers. 2013. Consistent assignment of nursing staff to residents in nursing homes: A critical review of conceptual and methodological issues. *The Gerontologist* 55:434–47.

Sabety, A. 2023. The value of relationships in healthcare. *Journal of Public Economics* 225.

Sabety, A. H., A. B. Jena, and M. L. Barnett. 2021. Changes in health care use and outcomes after turnover in primary care. *JAMA Internal Medicine* 181:186–94.

Schwab, S. 2023. The value of specific information: Evidence from disruptions to the patient-physician relationship. *Management Science* Revise and Resubmit.

Shen, K., B. E. McGarry, and A. D. Gandhi. 2023. Health care staff turnover and quality of care at nursing homes. *JAMA internal medicine* 183:1247–54.

Shen, K., B. E. McGarry, D. C. Grabowski, J. Gruber, and A. D. Gandhi. 2022. Staffing patterns in us nursing homes during covid-19 outbreaks. *JAMA Health Forum* 3:e222151–.

Smith, D. M. 1995. Pressure ulcers in the nursing home. *Annals of Internal Medicine* 123:433–42.

Soergel, A. 2020. Nursing homes are getting billions in covid aid – where is it going? *AARP* https://www.aarp.org/caregiving/health/info-2020/nursing-home-covid-federal-aid-transparency.html.

Thomas, K., R. Gebeloff, and J. Silver-Greenberg. 2021. Phony diagnoses hide high rates of drugging at nursing homes. *The New York Times* .

Tolson, D., and J. E. Morley. 2012. Physical restraints: Abusive and harmful. *Journal of the American Medical Directors Association* 13:311–3. doi:10.1016/j.jamda.2012.02.004.

Trinkoff, A. M., C. L. Storr, N. B. Lerner, B. K. Yang, and K. Han. 2017. Cna training requirements and resident care outcomes in nursing homes. *The Gerontologist* 57:501–8.

U.S. Senate. 1960. The condition of american nursing homes: A study by the subcommittee on problems of the aged and aging. Congressional Report 86th Congress, Committee on Labor and Public Welfare, Washington, DC.

———. 2024. The long-term care workforce: Addressing shortages and improving the profession. Congressional Hearing 118th Congress, Special Committee on Aging, Washington, DC.

Wasson, J. H., A. E. Sauvigne, R. P. Mogielnicki, W. G. Frey, C. H. Sox, C. Gaudette, and A. Rockwell. 1984. Continuity of outpatient medical care in elderly men: A randomized trial. *JAMA* 252:2413–7.

World Bank. 2025. Gdp. https://data.worldbank.org/indicator/NY.GDP.MKTP.CD. Accessed: 2025-02-13.

A Survey Experiment Appendix

This appendix provides further details regarding our online survey experiment. In Section A.1, we describe the experiment design. In Section A.2, we provide details regarding our statistical analysis of the experiment data and the corresponding results. In Section A.3, we present additional survey results elucidating the mechanism by which a bankruptcy causes nurse turnover.

A.1 Experiment Design

We use a platform called Lucid to survey a participant sample consisting exclusively of nurses. We first screen applicants using attention tests. These are questions with answers that are obvious if and only if the participant reads carefully. We exclude participants that fail these attention tests. Next, we ask screening questions to ensure that the participant: (i) has worked in the healthcare industry; (ii) has worked as either a LPN, CNA, or RN; and (iii) has worked at a nursing home (skilled nursing facility). We record the highest paid nursing role that the participant has held (i.e., if a participant has worked as both a RN and a LPN, we record RN). We refer to this as the participant's prior nursing role.

A.1.1 Part 1: Hypothetical Patient-Care Scenarios

In the first part of the experiment, participants read descriptions of hypothetical patient-care scenarios. Each scenario involves a specific set of tasks that a nurse must complete for a specific hypothetical patient. Consider the following example:

> Sally Conner is a 75 year old diabetic who recently suffered a stroke at home. She has left-sided weakness in her arm and leg, and currently spends most of her time in bed.
>
> Imagine that Mrs. Conner has been moved into a skilled nursing facility for recovery and needs her daily vital signs assessed: blood pressure, heart rate, vision, temperature, glucose levels, and weight.

After reading the description, the participant estimates how long they personally would take to complete the tasks. This helps the participant estimate a concrete completion time. We next ask the participant to estimate completion times for the same tasks for two hypothetical nurses. One nurse, "Nurse Smith," has two years of tenure at the facility. The other nurse,

"Nurse Williams" has a shorter tenure at the facility. Each participant reports estimated completion times for both nurses.

In theory, participants might infer that they are supposed to care about the length of tenure at a facility. Importantly, our main specification does not compare a given participant's responses for one nurse to the same participant's responses for the other nurse. Instead, we randomize the length of tenure for "Nurse Williams" *across* participants and compare completion-time reports across participants. Specifically, half of participants see that Nurse Williams has one year of tenure at the facility. The other half are told that Nurse Williams has one week of tenure at the facility. Once a participant is randomized into a Nurse-Williams-tenure level, they see the same Nurse-Williams description in all scenarios they evaluate. Comparing responses for Nurse Williams across participants, we can thus exogenously vary a nurse's length of tenure without leading participants to think this variation is important.

In other words, even if a participant thinks they are supposed to report a longer completion time for the shorter-tenure nurse, they cannot possibly believe they are supposed to report a longer completion time than other participants who were randomly assigned a longer-tenure nurse. We use reported completion times for the longer-tenured nurse, Nurse Smith, only to control for idiosyncratic beliefs about completion times. Comparing average reported completion times for Nurse Williams across the two randomized groups, we estimate the effect of employee tenure on task-completion efficiency.

We use a similar approach to evaluate the impact of employee tenure on task-completion quality. For each scenario, each participant evaluates the likelihood that an adverse outcome would occur if they were to complete the tasks. To make this concrete, we give examples of adverse outcomes that could occur. For example, for the above scenario, we write the following:

> In completing the above tasks, potential mistakes or bad outcomes include: (i) incorrect or incomplete documentation of vital signs; (ii) not following proper hand hygiene, such as not washing or sanitizing hands and not using new, sterile gloves.

Just as for completion times, each participant then reports the likelihood of an adverse outcome if the task were completed by a hypothetical nurse.[20] Participants provide answers

[20]We ask participants to report how likely they believe it is that an adverse outcome will occur, on a scale from 0 (no chance of occurring) to 100 (certain to occur), if the task is performed by him or herself, Nurse Smith, or Nurse Williams.

for the same nurses and see the same randomized length of tenure for the less experienced nurse. Comparing responses across participants, we estimate the effect of employee tenure on the likelihood of an adverse patient outcome.

Each survey participant reads three descriptions of hypothetical scenarios, answering the above questions for each scenario. We use each participant's prior nursing role (e.g., RN or LPN) to select which tasks they see. For example, participants with LPN experience see scenarios describing tasks that would be performed by a LPN.

A.1.2 Part 2: Bankruptcy and Hypothetical Nurse Departures

In the second part of the experiment, participants read about a hypothetical nursing job at a hypothetical facility and estimate the rate of voluntary attrition at the facility.

To begin, participants provide details about their most recent nursing home job: the position, wage, and the state in which the facility was located. We also ask the participant to estimate what fraction of employees voluntarily leave that employer each year. The response to this question is used to control for the participant's idiosyncratic beliefs about voluntary worker attrition.

Next, for each participant, we construct a hypothetical job with the same position, wage, and location (state) as the participant's prior job.[21] Each participant then reads a description of the employer in the hypothetical job. Importantly, participants are randomly assigned to see different descriptions of the financial health of the employer. One third of participants see a "Control" description in which the employer is solvent:

> Facility A's revenue is large enough to pay for both its operating expenses (e.g., wages) and other financial obligations (e.g., annual debt payments).

One third of participants see a "Distressed" description in which the employer has a 25% chance of filing for Chapter 11 bankruptcy in the next year. Within this Distressed group, half of participants see a description of a "Profitable Distressed" employer:

> Facility A's revenue is large enough to pay for its operating expenses (e.g., wages), but is not enough to also fully pay its other financial obligations (e.g., annual debt payments). Facility A has a 25% chance of filing for Chapter 11 bankruptcy in the next year.

The other half of the Distressed group sees the following description of a "Baseline Distressed" employer:

[21] This controls for a participant's required job characteristics.

> Facility A has a 25% chance of filing for Chapter 11 bankruptcy in the next year.

In our baseline specification, we pool the "Baseline Distressed" and "Profitable Distressed" participants together. We let the indicator Distressed_i indicate whether a participant is in either of these two groups.

The final third of participants see a "Bankrupt" description in which the employer is currently open but has recently filed for bankruptcy. Within the Bankrupt group, half of participants see a description of a "Bankrupt Profitable" employer:

> Facility A's revenue is large enough to pay for its operating expenses (e.g., wages), but is not enough to also fully pay its other financial obligations (e.g., annual debt payments). While Facility A is currently open, it recently filed for Chapter 11 bankruptcy and is currently in bankruptcy proceedings.

The other half of participants in the Bankrupt group see a description of a "Baseline Bankrupt" employer:

> While Facility A is currently open, it recently filed for Chapter 11 bankruptcy and is currently in bankruptcy proceedings.

In our baseline specification, we pool the "Baseline Bankrupt" and "Profitable Bankrupt" participants together. We let the indicator Bankrupt_i indicate whether a participant is in either of these two groups.

After each participant reads the hypothetical job description, we ask them to imagine they are currently working in this position for this hypothetical employer. We then measure two key dependent variables. First, each participant reports the likelihood they would search for another job rather than continue working in this position. Second, each participant estimates the fraction of employees they believe will voluntarily leave the employer this year. As above, we compare responses across participants in different randomly assigned groups to estimate causal effects without biasing participants toward particular responses.

A.1.3 Sample Selection

We exclude individuals that fail attention checks. Additionally, we exclude individuals that have never worked in the healthcare industry at a skilled nursing facility as an RN, LPN, or CNA. We also exclude participants who do any of the following: (i) report a probability above 100, (ii) report a time to complete a task above four hours, (iii) report a historical

wage greater than $100 per hour, or (iv) give answers that are self-contradictory in the following manner: For each participant, we average their reported time for Nurse Williams to complete tasks across the three scenarios/patients. We do the same for Nurse Smith. At the end of the first part of the survey, we ask participants whether, on average, they think Nurse Smith is slower than Nurse Williams, faster than Nurse Williams, or the same speed. If the answer to this question is not "same speed" and is inconsistent with the participant's reported times, we drop the participant. For example, we drop a participant if their average reported completion time for Nurse Williams is 45 minutes, their average reported time for Nurse Smith is 20 minutes, yet they say on average Nurse Williams is faster than Nurse Smith.

We apply the analogous filter for the reported likelihood of an adverse patient outcome or mistake. For example, we drop a participant if their average reported likelihood of a mistake is 50% for Nurse Williams and 25% for Nurse Smith, yet they say that Nurse Smith makes more mistakes.

A.2 Statistical Analysis of our Experiment

A.2.1 Turnover Harms the Quality and Efficiency of Patient Care

To begin, we analyze the importance of employee turnover using the first part of the experiment (Section A.1.1). We let $j = 1, 2, 3$ index the hypothetical patient scenarios considered by each participant i. We let $k \in \{RN, CNA, LPN\}$ index the job that participant i previously held at a facility.[22]

Recall that in each scenario j, each participant i considers the performance of two hypothetical nurses. The longer-tenured "Nurse Smith" has been at the hypothetical facility for two years. The shorter-tenured "Nurse Williams" has been at the facility for less time: we randomize her tenure to be either one year or one week. Once a participant is randomized into seeing one of these two tenure levels, that participant sees the same tenure level in all questions.

To measure the importance of employee turnover, we compare participant evaluations of the one-week-of-tenure nurse to those of the one-year-of-tenure nurse. This is thus a comparison across participants. Since tenure levels are randomized, we evaluate the causal effect of replacing a nurse who has worked at a facility for one year with a nurse who has

[22]If a participant reports that they have worked in more than one of these roles, we use the one with the highest required level of training.

worked there for one week. Specifically, we estimate the following regression by OLS:

$$\text{Task Completion Time}_{ijk} = \alpha_j + \alpha_k + \delta \text{Turnover}_i + \gamma \text{Perceived Task Difficulty}_{ij} + \epsilon_{ijk}. \quad (9)$$

In this equation, an observation is a participant i with prior job k evaluating a particular scenario j. We include fixed effects α_j and α_k for the hypothetical scenario j and the participant i's prior job k. Task Completion Time is the reported completion time for the shorter-tenured nurse. Turnover is an indicator for participant i being randomly selected to consider a nurse with one week, rather than one year, of tenure. Finally, Perceived Task Difficulty is the reported completion time for the longer-tenured nurse; As discussed in Section A.1.1, we only use participant responses for the longer-tenured nurse to control for idiosyncratic participant beliefs about task difficulty. We cluster standard errors at the participant level.

Finally, we estimate a similar regression to study the effects of turnover on the quality of patient care. Recall that each participant evaluates the likelihood of a mistake or bad outcome in each scenario. We use these responses to estimate the following regression by OLS:

$$\text{Rate of Mistakes}_{ijk} = \alpha_j + \alpha_k + \delta \text{Turnover}_i + \gamma \text{Perceived Task Risk}_{ij} + \epsilon_{ijk}. \quad (10)$$

In this equation, Rate of Mistakes is the reported likelihood of a mistake or bad outcome for the shorter-tenured nurse. Perceived Task Risk is the reported likelihood of a mistake or bad outcome for the longer-tenured nurse. Turnover is once again an indicator for participant i being randomly assigned to evaluate a shorter-tenure nurse with only one week of experience at the hypothetical facility.

Panel A of Table A1 presents our OLS estimates of equations (9) and (10). According to the nursing staff we survey, turnover reduces the efficiency and quality of patient care. Comparing participants who evaluate a nurse with one week of facility tenure to those who evaluate a nurse with one year of facility tenure, the nurse with one week of tenure takes 6.2 minutes longer to complete tasks on average. This represents an increase equal to 14% of the control-group average completion time. Likewise, the nurse with one week of tenure has a higher likelihood of mistakes or bad outcomes - the rate increases by 9.7 percentage points on average, 44% of the control-group mean.

A.2.2 Bankruptcy Increases Turnover Through Voluntary Employee Departures

Next, we evaluate how a firm's bankruptcy or financial distress affects the willingness of employees to work for that firm. As described in Section A.1.2, each participant i considers a hypothetical job. Participants are randomly assigned to view different descriptions of the employer. Each participant then reports the likelihood that they would search for another job if they currently had this hypothetical job. Participants also estimate the fraction of employees that would voluntarily leave this employer this year. Using these participant responses, we estimate the following regressions:

$$\text{Voluntary Departure}_{ik} = \alpha_k + \beta \text{Distressed}_i + \delta \text{Bankrupt}_i + \text{Turnover Belief}_i + \epsilon_{ik} \quad (11)$$

$$\text{Departure-Rate Guess}_{ik} = \alpha_k + \beta \text{Distressed}_i + \delta \text{Bankrupt}_i + \text{Turnover Belief}_i + \epsilon_{ik}. \quad (12)$$

In this equation, an observation is a participant i with prior job k. Voluntary Departure is the likelihood that participant i would search for another job if they held this hypothetical position. Departure-Rate Guess is participant i's estimate of the percentage of workers that will voluntarily leave this hypothetical employer this year. Distressed is an indicator equal to one if participant i is randomly assigned to evaluate a hypothetical job for a financially distressed employer - one with a 25% chance of filing for bankruptcy in the next year. Bankrupt is an equivalent indicator for being randomly assigned to consider a bankrupt employer. We omit the indicator for the control group. Finally, Turnover Belief is participant i's estimate of the percentage of workers that voluntarily left participant i's prior employer each year. We use robust standard errors.

Panel B of Table A1 presents OLS estimates of equations (11) and (12). Panel B demonstrates that both bankruptcy and financial distress dramatically decrease willingness to work at a facility and likely increase voluntary worker separations. Specifically, bankruptcy increases the participant's own likelihood of searching for another job by 28.8 percentage points (75% of the control-group mean), while financial distress increases the likelihood by 25.3 percentage points (66% of the control-group mean). Bankruptcy and distress also increase participants' perceived rates of voluntary attrition by 18 (47% of the control-group mean) and 7.5 (20% of the control-group mean) percentage points, respectively.

Table A1: Results from Online Randomized Experiment on Nursing Staff

Panel A: Effect of Turnover on Task Efficiency and Quality of Care

	Completion Time	Completion Time	Mistake Rate	Mistake Rate
New Hire	6.211***	6.209***	9.666***	9.668***
	(1.516)	(1.517)	(2.099)	(2.102)
Task Difficulty	1.177***	1.180***		
	(0.047)	(0.047)		
Task Risk			0.818***	0.816***
			(0.038)	(0.038)
FE: Job	Yes	Yes	Yes	Yes
FE: Scenario	No	Yes	No	Yes
R^2	0.86	0.86	0.52	0.52
Clusters	247	247	247	247
Control Mean	43.03	43.03	22.13	22.13
Observations	741	741	741	741

Panel B: Effect of Bankruptcy on Job Search and Attrition

	Probability You Job Search	Probability You Job Search	Probability Others Voluntarily Separate	Probability Others Voluntarily Separate
Bankrupt Pool	28.810***	29.741***	17.972***	19.203***
	(5.140)	(4.841)	(3.618)	(2.959)
Distressed Pool	25.295***	27.666***	7.481**	10.615***
	(5.125)	(4.972)	(3.604)	(3.008)
Baseline Turnover		0.431***		0.569***
Belief		(0.091)		(0.058)
FE: Job	Yes	Yes	Yes	Yes
R^2	0.15	0.23	0.13	0.41
Control Mean	38.48	38.48	37.97	37.97
Observations	244	244	244	244

Note. **Panel A:** Each participant is asked three questions about the care provided by Nurse Williams and Nurse Smith to different patients. The tenure of Nurse Williams is randomized over {One Week, One Year} with equal probability across participants. The dependent variable Completion Time denotes participant belief of the number of minutes Nurse Williams takes to complete the task. The dependent variable Mistake Rate denotes participant belief of the probability of a bad outcome or mistake if Nurse Williams undertakes the task. Standard errors in parentheses are clustered at the participant level. **Panel B:** Participants are randomized into Control, Bankrupt, and Distressed with probabilities 1/3, 1/3, and 1/3, respectively. The dependent variables are the participant's reported likelihood of searching for another job and the perceived voluntary worker attrition rate from the facility. Robust standard errors in parentheses. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

A.3 Mechanisms

After participants answer questions regarding their willingness to work at Facility A, we collect survey evidence from those in the treatment groups (Bankrupt or Distressed) about the specific concerns that affect their decisions. We ask participants to rate four specific concerns on a scale from 1 (not at all concerned) to 7 (very concerned). Table A2 displays the average ratings reported for the four concerns. Every concern has an average rating above 4, the neutral rating. The strongest concern that participants have is that the facility's financial problems would cause it to close down, forcing them to find another job. The second strongest concern is that the facility would reduce wages.

We also ask participants to share in their own words any concerns that may have influenced their willingness to stay. Appendix A.3.1 contains the free responses in their raw form. Consistent with the numerical ratings, many participants report concerns about job security, the facility closing down, and wages. However, the free responses also bring some additional insights. Some participants express direct concerns with working for a facility that was potentially poorly managed (either financially or operationally):

> *"For a nursing facility to file for bankruptcy or have any type of financial troubles is an immediate red flag. It could mean poor leadership or weak business management. I would have no interest in working for any company like that."*

Other participants indicate that the financial condition of the facility wasn't a direct consideration, but that their primary concern was the facility being short-staffed. Many participants specifically report concerns about the consequences of other workers leaving (e.g., on team dynamics), and particularly that departures of existing workers mean that those who remain would be left to train new hires and become overworked. For example:

> *"I'd be afraid the experienced workers would find other jobs and we would be training mostly brand new employees."*

Within the Distressed group, participants have relatively mixed responses. Some further emphasize concerns related to wages and shutting down. Some state that as long as the facility provided adequate pay, the firm's financial distress would not cause them to search. Similarly, some express that a 25% chance of bankruptcy was not high enough to leave, and that they would not search for a new job until problems started occurring.

Table A2: Concerns Influencing Willingness to Work at Facility

	Bankrupt		Distressed		All Treated	
	mean	sd	mean	sd	mean	sd
SNF will close down	5.56	1.58	5.47	1.63	5.52	1.60
Sign of poor-quality SNF	4.80	1.50	4.88	1.54	4.84	1.51
SNF will reduce my wage	5.15	1.50	5.35	1.58	5.25	1.54
Will be unpleasant	5.06	1.44	4.87	1.70	4.97	1.57

Note. Participants in the treated groups rank four potential concerns about working at a bankrupt or distressed facility on the following scale from 7 to 1: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, and strongly agree. The full text of the four concerns are: (i) I am concerned that Facility A's financial problems will cause it to close down, forcing me to find another job. (ii) I am concerned that Facility A's financial problems are a sign of a poor-quality facility. (iii) I am concerned that Facility A's financial problems will cause it to reduce my wage. (iv) I am concerned that Facility A's financial problems will make working there unpleasant.

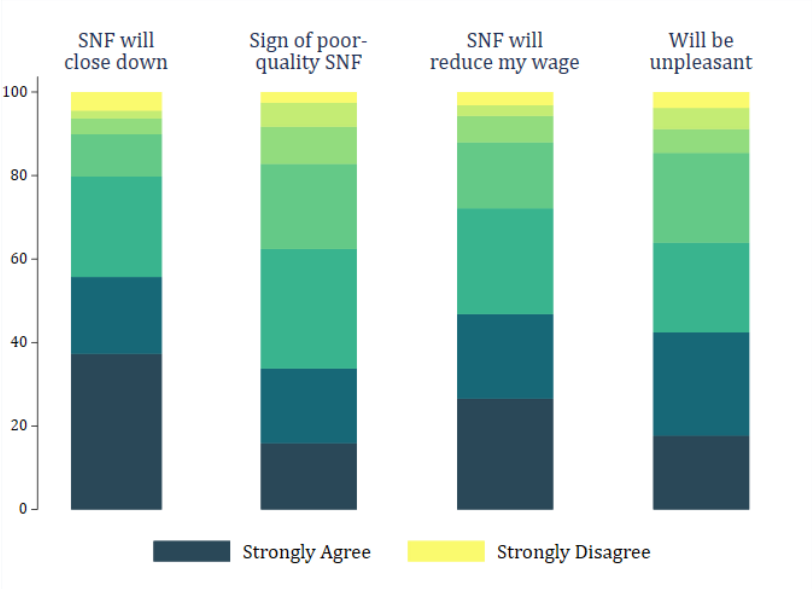


Figure A1: Concerns Influencing Willingness to Work at Facility

Note. Participants in the treated groups rank four potential concerns about working at a bankrupt or distressed facility on the following scale from 7 to 1: strongly agree, agree, somewhat agree, neither agree nor disagree, somewhat disagree, disagree, and strongly agree. The full text of the four concerns are: (i) I am concerned that Facility A's financial problems will cause it to close down, forcing me to find another job. (ii) I am concerned that Facility A's financial problems are a sign of a poor-quality facility. (iii) I am concerned that Facility A's financial problems will cause it to reduce my wage. (iv) I am concerned that Facility A's financial problems will make working there unpleasant.

A.3.1 Concerns Influencing Willingness to Work: Participant Free-Text Responses

All responses have been kept in their original form, including spelling or grammatical errors. Responses are presented in descending order by length.

Bankrupt Group

- Any job I work is based on financial needs and passion. I have a passion for caring for others and certainly would feel sympathetic to the faculty and patients, however in the end, I have a family to care for and bills that have to be paid. A good raise would certainly extend my stay, and possibly less than $5 raise would be considered, but ultimately, it would be a see and tell situation. Even with a raise, I would likely be looking around elsewhere for a backup plan.
- Just because they have financial problems does not mean that it was a bad facility. It does not mean that the workers are not dependable and good workers. It does not mean that the residents are bad. Some companies just go through financial hardships and they work their way out of it. I would give a chance to see if that would happen before I would leave if I enjoyed my job my coworkers and enjoyed working with the residents
- Facility A clearly has serious challenges with management - either someone is making bad financial decisions, overhead is too high or patient selection is ineffective. Since they've already filed for bankruptcy, the writing is on the wall with this facility and I wouldn't stick around to find out how quickly the doors will close.
- If I chose to stay it would be hard because during bankruptcy so many things could happen and leave you with no job and a roof over your head. If I would stay they would have to offer me a significant amount of money and the residents would have to be so very special that I didn't want to go
- With this type of news, filing for chapter 11, it's highly unlikely I would remain. I don't see much influence for me to stay. I may show up one day and the doors are locked. I can't have that happen so to be proactive and initiate another job, is in my best interest.
- finding a position elsewhere if facility A closes, would want to locate a position just in case. would like to know if there are any potential buyers for the facility and who they are, past facilities and their success in business, ratings, etc.
- For a nursing facility to file for bankruptcy or have any type of financial troubles is an immediate red flag. It could mean poor leadership or weak business management. I would have no interest in working for any company like that
- with increased costs of operating any healthcare facility now, I do not see financials as the biggest factor in people leaving. I think worker shortage and lack of teamwork as a bigger factor for people leaving the work place.
- It depends on the amount of time I've put in for work at the facility and how close I am with the residents. It's hard to leave a facility once you've been there for so long
- I would not leave a facility just because it filed for bankruptcy. I evaluate the facility on the quality of care and the teamwork ability of the employees.
- They have been good to me so I would be reluctant to look for a nother job because you form a relationship with your coworkers and become like family
- If Facility A goes bankrupt, I'm for sure without a job, and even though the hourly wage is good, I'd rather not have to worry about losing my job.

- North Carolina's minimum wage is awful as it is but being a CNA and the pay is even not worth being one. Been ready to leave this job long ago
- If unable to manage finances how are they able to properly manage everything else that is required for a facility to be ran safely.
- If finances are in trouble supplies may be inadequate. Staffing is likely to be the legal minimum leaving an impossible workload.
- The possibility of it closing down due to it's financial problems and then I would have to search for a job anyway
- im afraid they will cut the amount of workers they use to save money and they will be overworked and short staffed
- I would work at Facility A if the pay is good and that it would help me pay anything like rent or something else.
- I'd be afraid the experienced workers would find other jobs and we would be training mostly brand new employees.
- My concern would be that there would not be enough supplies to maintain adequate care needed for the residents.
- Cause the money is there to pay the wages and alit of facilities have problems but there not always on going
- The residents that live there are a joy to work with as well as my coworkers and the hourly pay is decent.
- Read all the responses above. This is not a surprise in the healthcare field. Let alone in ALF's or SNF's
- They may not tell people they are losing their jobs until the last minute to prevent them from quitting.
- Not receiving paycheck on time. Not receiving enough hours. Not receiving any health benefits.
- If they can't afford or manage the money to run a skilled place how will I know I can get paid
- Loyalty to staff, management and clients. I can always (later) find another job in nursing.
- The patients or residents are not getting the proper care they need due to short staffing
- I would be fearful of losing my employment there. I need health benefits for my children.
- I enjoy my job, co-workers, and residents I would stick by them as long as I could
- To try and make the situation better, but if they bankrupt I would not stay
- Would want to see if someone would buy the Facility and turn things around
- That the residents living there will always need help with daily living.
- I love my job my clients and workers I've been with them for 8 years
- Being unsure of the potential outcome once bankruptcy is completed.
- That the facility is filing bankruptcy and possibly closing down.
- The residents in the facility still need to be taken care of
- The residents and the relationships I get to build there.
- Just the overall treatment of workers and also the wages
- for the care of the residents that you become bonded to

- The patients that you grow close to and need good care
- I would willingly stay if I was promised an incentive.
- Job security, financial security, and quality of care.
- I hope I can contribute to making it a better place
- It may be that there is poor leadership at the top?
- The supplies and staff needed to provide good care
- The residents still need people to care for them.
- It is having financal issues and could shut down.
- I feel that they will cut my hours and pay rate.
- i have no concerns at this time for facility A
- None because they are having financial issues
- Closeness to home, relationships to coworkers
- Concern for the residents care and wellbeing
- Loyalty. And tonprovide good patient care
- Instability and fear of financial worries
- concerned they would cut down on staff
- I love the people and co workers there
- Not finding someone who truly cares
- The residents still need help
- Better pay better faciliry
- Starting over at a new job
- To stay for the residents
- The residents and staff.
- Getting a pay check
- Fear of losing job
- That there closing
- Chance of closing
- I love the work
- The atability
- Wage per hour
- Nothing much
- I don't know
- Higher wage
- No concerns
- Nothing

- Finance
- The pay
- Wages
- N/a
- B

Distressed Group

- Jobs for nurses are a dime a dozen. I will not stay at a facility that is financially unstable - unless they are paying me so much that I couldn't possibly leave. Even then, my attitude would suck and I'd view it as a short-term position until the facility failed.
- I have concerns that it may have to close down leaving me without a job. I am also concerned that it will cause stress in our working environment which isn't fair to the residents if we cannot do our jobs properly.
- For me to work at a nursing home first and foremost the patients have to be well cared for they must always be number one priority. Next the past must be decent and comparable to other facilities in the area.
- If I was assured the facility would be able to keep the doors open, and that wages and benefits are still being paid. I would also worry about shortcuts being taken with patient care and medical supplies.
- The location and distance between work and home. Flexibility and benefits. Opportunities for advancement. Positive staff/resident and work environment and good working relationships
- As long as they don't start making shortcuts to patient care I'm good. When staff cuts, lack of supplies, crappy food trays, etc start happening I am gone no matter what the pay!
- I would want to make certain My wages would not decrease and conditions are good to work in. I also make definitely sure that we would have enough help for the residents
- My main concern is the facility may not be fully forthcoming and things may be worse than suspected. It is possible I shoe up to work one day and the door is locked.
- If it's going under chances are management is going to treat the employees bad and residents will feel that and they'll become hostile especially memory care
- Patients still need care no matter if the facility declares bankruptcy or not. If to many workers leave, the patients don't receive the care that is needed.
- The bankruptcy issue therefore that would affect my pay eventually and then closing down so then I will that will leave me with not having a job
- Because it's only a 25 percent chance of filling for bankruptcy. So there's still a very good chance of 75 percent that it won't happen.
- My concerns would be having to drive a distance for another job as well as the bond that I have with the residents at the facility.
- I don't understand. Why would concerns influence me to work at this facility. Wouldn't concerns cause me to leave?
- Relationship with residents and staff. May be convenient to my home. Knowing the systems in that facility.
- The pay rate and the fact that it's only a 25
- There's only a 25

- Being afraid of a pay cut in order for them to obtain their own bills or a potential shutdown
- Job security and the possible reduced level of care as a result of poor financial management.
- I don't like to change jobs frequently... Prefer to establish trust with patients in a SNF.
- The people I work with, the nurse patient ratio, the type of duties I need to perforn
- Once my hourly wage was raised I didn't have any concerns with staying at facility A.
- reduced wages, unpleasant working environment, decrease in quality of care provided
- It might b a decent place to work but it wouldnt pay as much as other better places
- How well it works for the client and how well they at and train the new employees
- I would be concerned that they may be closed down if they can't pay their bills.
- Residents not receiving proper care and employees being overworked and underpaid
- I would work there until problems start occurring then I would find another job
- The money in working in that facility. Having the help they truly need for it.
- I'm afraid they try to cut down expenses and doing that make my work harder
- The residents still need help regardless if they are closing soon or not
- I don't want to suddenly be without a job or with a very diminishes wage
- Feeling of helping people. Making a positive impact on people lives
- Low pay & possible bankruptcy percentage increase in upcoming years.
- It pays good and the fact I just love taking care of residents
- Not much they don't seem like the greatest company to work for
- The money bit of they are in financial trouble I'm leaving
- I care about the patients on my unit and my coworkers.
- I want to stick out out but not otf they can't pay me
- Loyalty and waiting to see what the outcome would be
- If they pay more I would definitely work with them
- Not sure I would stay, depends on circumstances
- I lovw the job and the people i work with
- Their financial situation is a red flag
- The fact they are in financial trouble.
- Worried about the system shutting down.
- They have patients who need cared for
- Not enough staff, not enough supplies
- The facility going into bankruptcy
- Good facility and work environment
- financial status and job stability
- The need of care for the patients

- 25
- I would stay for the residents.
- They seemed very promising.
- It's a lot going on their.
- No other options available
- The care of the residents
- Their financial problems
- The care of the patients
- Care of the patients
- Everyone needs help
- It was close by
- Needed income
- pay my bills
- Nothing
- Unsure
- Shift
- N/a

B Data Appendix

B.1 Matching Bankruptcies to Facilities

We begin with the universe of corporate Chapter 11 bankruptcy filings over the period from January 1, 2010 to March 31, 2020. We exclude the period before 2010 due to data limitations. We exclude the period after March 2020 to avoid COVID-driven bankruptcies. We focus on Chapter 11 bankruptcies because Chapter 7 cases lead to 100% employee attrition by definition. We collect 66,121 corporate Chapter 11 bankruptcies over this period from Bankruptcydata.com.

We exclude a small fraction of bankruptcies in which the EIN is missing or a unique case identifier is not provided. This leaves us with 59,266 bankruptcies. We focus on the first filing date for any EIN to avoid studying refilings, in which employees may already be primed by the earlier bankruptcy. This excludes 4,000 bankruptcies, leaving us with 55,266 bankruptcies.

We then merge these bankruptcies to NPIs using a map provided by CMS. The map from CMS has the EIN for every type-2 provider (e.g., business) with an NPI. In some instances, the map also has the EIN of the parent company of the provider. Finally, the map sometimes contains historical EINs or parent EINs for NPIs that have changed their EIN or parent EIN over time. We focus attention on NPIs associated with nursing homes. To do this, we first merge our CMS-provided map with a list of all NPIs associated with facilities in the Minimum Data Set (MDS).

We match bankruptcies to facility NPIs by EIN in steps. Specifically, we order EINs in the CMS-provided map as follows: 1. current EIN; 2. current parent EIN; 3. historical EINs, going from most recent to least recent; 4. historical parent EINs, going from most recent to least recent. We match NPIs to bankruptcies using the first EIN in this ranking, the current EIN. For NPIs that do not match any bankruptcy by this step, we match those NPIs to bankruptcies by the second EIN in the ranking (parent EIN). We repeat this process moving down the above ordering. In each step, we match the following number of NPIs: 1. 535 NPIs match by current EIN; 19 NPIs match by current parent EIN; 48 NPIs match by historical EIN; 1 NPI matches by historical parent EIN. We thus match 603 NPIs by EIN.

Our list of facility-associated NPIs also includes all provider IDs, the identifier from the POS and PBJ datasets, associated with each NPI. In instances where multiple provider-ids are associated with an NPI, we manually check that the addresses and names match in the NPPES and POS databases. We exclude a small handful of incorrect NPI - provider ID

associations in which the names and addresses do not match, likely due to a typo when the healthcare provider inputted the provider ID. This process identifies 568 provider IDs associated with the 603 NPIs that we match to bankruptcies.[23]

Next, we group together jointly administered bankruptcy cases. For jointly administered cases, Bankruptcydata.com has a variable indicating the name of the lead case. We call two bankruptcies jointly administered if they have the same value for the lead case. Likewise, the Federal Judicial Center (FJC) database has a coded variable identifying the lead case for any jointly administered case. We supplement the Bankruptcydata.com lead-case classification with the FJC lead-case classification. In instances where there is a conflict, we resolve the conflict by checking PACER. Specifically, when we are unsure what the lead case is for a particular bankruptcy, we go to the PACER page for that bankruptcy and check either the list of associated cases or motions for joint administration or the filing petition to find the full set of cases that are jointly administered in that case. Within a collection of jointly administered cases, we rely on the same method to determine which is the lead case. Finally, we manually inspect the final set of bankruptcies to ensure that Bankruptcydata.com and FJC do not miss any instances in which two cases are jointly administered. This involves checking cases filed in the same court with similar filing dates or similar names, then going to PACER and verifying the set of jointly administered cases by the same method described above. Within a set of jointly administered cases, we define the filing date as the earliest filing date of any of the jointly administered cases. In most instances, all jointly administered cases share the same filing date.

We then verify that each NPI is associated with at most one collection of jointly administered bankruptcies. This process reveals that one chain, Bloomfield Nursing Operations, sold off all of its facilities to Preferred Care (a chain that later filed for bankruptcy) prior to Bloomfield's bankruptcy. We thus drop the Bloomfield Nursing bankruptcy. Likewise, we confirm that each facility was not involved in an earlier bankruptcy under a different lead case. This leads to a slightly lower number of NPIs.

Next, we go through large bankruptcies to ensure we did not miss anything. In some cases, a large bankrupt firm will have many subsidiaries, each of which file their own bankruptcy with their own EIN. In such cases, our EIN merge will correctly assign the subsidiaries' facilities to the large bankrupt firm. However, in other cases, a large bankrupt firm will operate many facilities itself. In these instances, if the parent EIN field is missing for the individual

[23]Sometimes a provider ID will have two NPIs associated with it in the NPPES. We verify that these two NPIs have the same name and address. Likewise, sometimes an NPI will have two provider IDs associated with it. We verify that these two provider IDs have the same name and address.

facilities, we could miss some facilities. To check for this, we manually inspect all of the 55,266 bankruptcies in Bankruptcydata.com that (i) list healthcare as their industry and (ii) have at least 100 million in liabilities. Using company descriptions from Bankruptcydata.com, first-day declarations, disclosure statements, and reorganization plans, we determine which of these companies operate nursing homes. For the companies that operate nursing homes, we use a combination of these same bankruptcy documents and SEC filings to locate the names and addresses of their facilities. For example, for HCR Manorcare, we use the master lease agreement to identify names and addresses of 245 facilities it operates. We then manually find these facilities in POS to obtain their provider IDs. We likewise use the following documents to identify facilities, which we then match to provider IDs in POS: a disclosure statement from CC Care listing facility names and addresses; a motion for joint administration from Preferred Case listing facility names; a disclosure statement from Orianna listing facility names; a disclosure statement from Senior Care Centers listing facility names.

Finally, we fuzzy merge our sample of bankruptcies by names and addresses to POS and manually inspect highly similar strings to ensure that names and addresses are identical (up to abbreviations). This adds a small number of matches. We assign these to jointly-administered-case clusters by inspecting bankruptcy documents as described above.

In the end, we identify 187 clusters of jointly-administered cases, covering 869 provider IDs and 598 NPIs. The lower number of NPIs is likely due to the fact that in our manual process of matching large bankruptcies, we only link to provider IDs to save time.

B.2 Staffing Data

Tenure Variables In the main text, we consider a tenure threshold of 60 days. Determining whether a worker's tenure exceeds this threshold requires at least 60 days of facility staffing data. To be conservative, we drop the first 13 weeks (approximately 90 days) of each facility's data. 13 weeks corresponds to approximately one reporting period since facilities report quarterly. Additionally, we identify rare cases in which a facility does not report staffing for an extended period; if a facility fails to report for nine weeks, we drop the subsequent 13 weeks of data. These "lookback period" restrictions are applied to all of the analyses with tenure- and turnover-related variables, leading to a smaller observation count in these regressions.

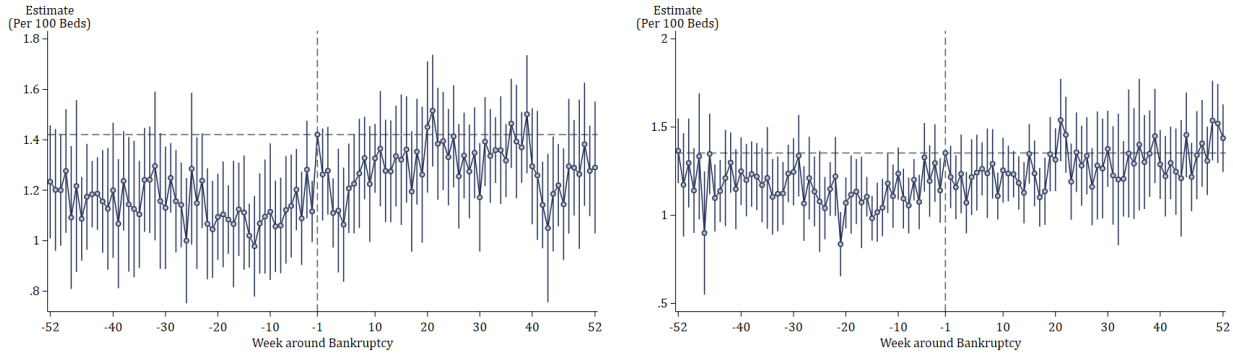
Software Changes While the PBJ data are generally very high quality, there are instances where the data indicate turnover of virtually all staff in a very short period of time. Based

on discussions with a large payroll/PBJ software vendor, we understand that these are likely instances in which a nursing home changed payroll/PBJ software without taking the appropriate steps to retain worker IDs. Since this distorts the measurement of worker tenure, we implement a procedure to flag such changes and remove them from the data. Specifically, we use a rolling window approach, recognizing that changes may take over a week to implement since shifts are often scheduled in two-week intervals. To be conservative, we measure observed turnover over a four-week period, ensuring we capture any potential software changes from facilities on monthly payroll. In other words, we calculate the share of total hours worked by employees who (appear to have) joined within the past four weeks. We then identify facility-weeks where all hours are supplied by these "new hires" and there are more than ten such workers. (For example, if a facility only has three workers, it is plausible that the facility had 100% turnover over a month rather than a software change). Once flagged, we exclude the facility's identified four-week software change period from the analysis. In addition, we exclude the 13 weeks (approximately 90 days) of the facility's staffing data following the software change period to ensure sufficient data to measure worker tenure.

C Staffing Analysis Appendix

C.1 Dynamic Tenure Figure

Figure C1: Dynamic Effects of Bankruptcy on Nursing Staff Turnover



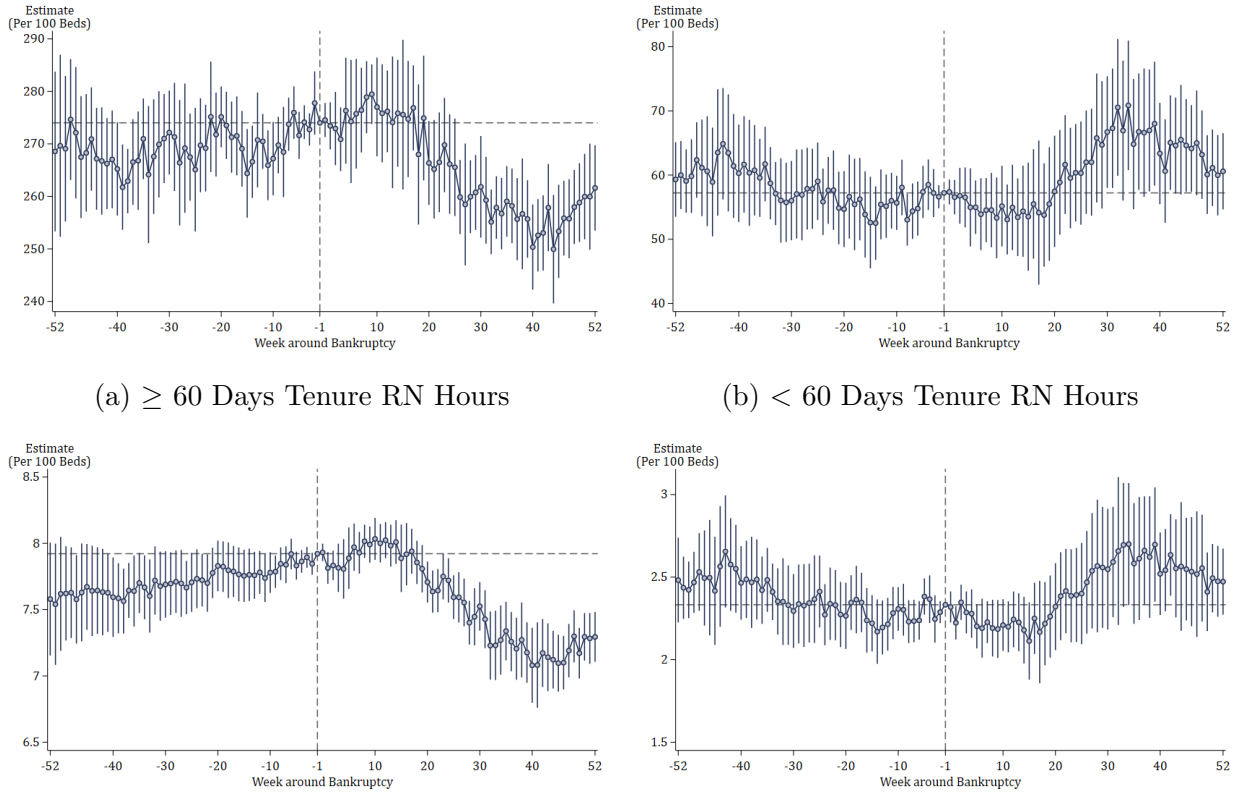
(a) Separations per 100 Beds

(b) New Workers per 100 Beds

Note. This figure examines staffing turnover around bankruptcy. The left panel shows total weekly nursing staff separations per 100 beds. The right panel shows total weekly new nursing staff per 100 beds. Standard errors are clustered by nursing home chain. 95% confidence intervals are shown. See Table 3 for point estimates.

C.2 Tenure Figures for each Nursing Staff Role

Figure C2: Dynamic Effects of Bankruptcy on Registered Nurse (RN) Staffing Tenure



(a) $\geq$ 60 Days Tenure RN Hours

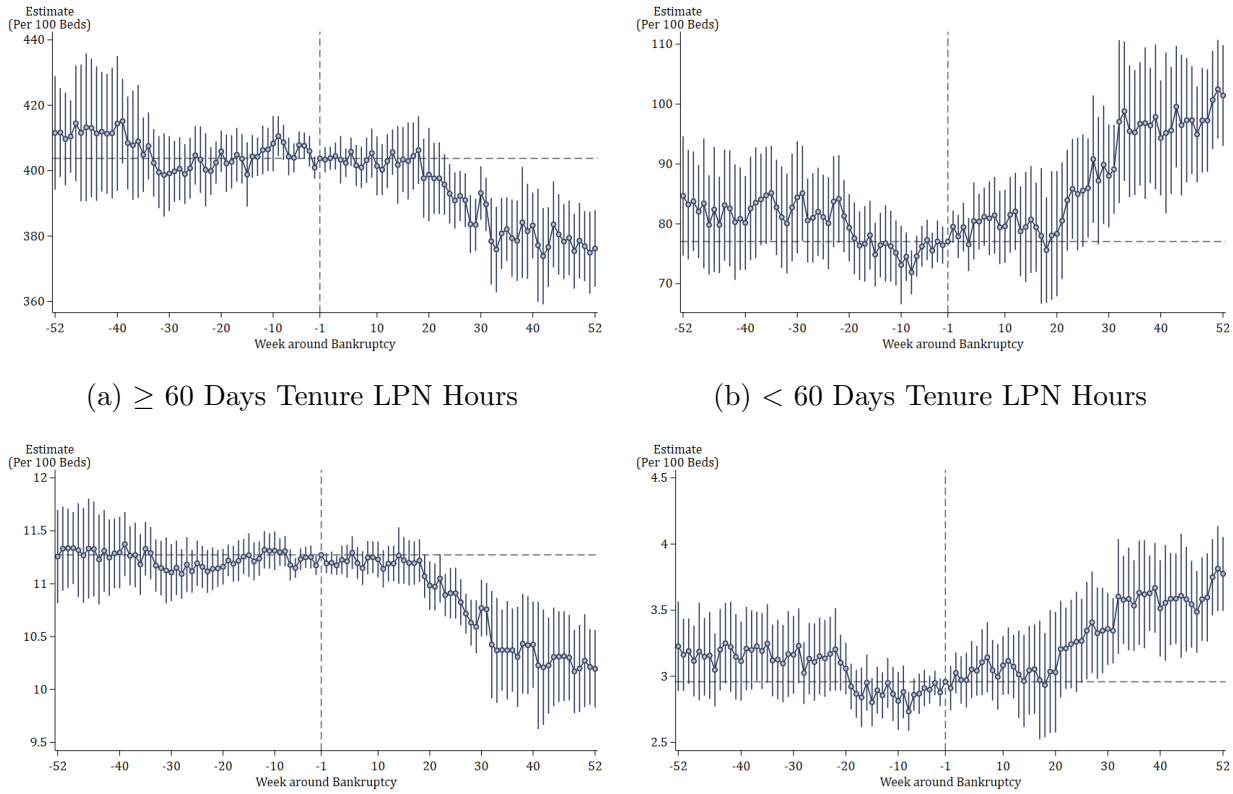
(b) $<$ 60 Days Tenure RN Hours

(c) $\geq$ 60 Days Tenure RNs

(d) $<$ 60 Days Tenure RNs

Note. This figure examines staffing by workers of different experience levels. The left panel shows total weekly (per 100 beds) RNs with at least 60 days of experience at the facility. The right panel shows total weekly (per 100 beds) RNs with fewer than 60 days of experience at the facility. Standard errors clustered by nursing home chain, and 95% confidence intervals are shown.

Figure C3: Dynamic Effects of Bankruptcy on Licensed Practical Nurse (LPN) Staffing Tenure



(a) $\geq$ 60 Days Tenure LPN Hours

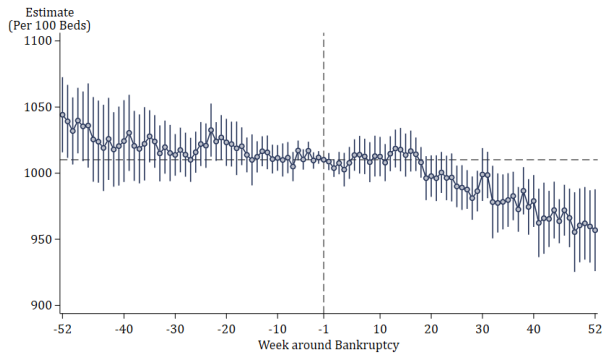
(b) $<$ 60 Days Tenure LPN Hours

(c) $\geq$ 60 Days Tenure LPNs

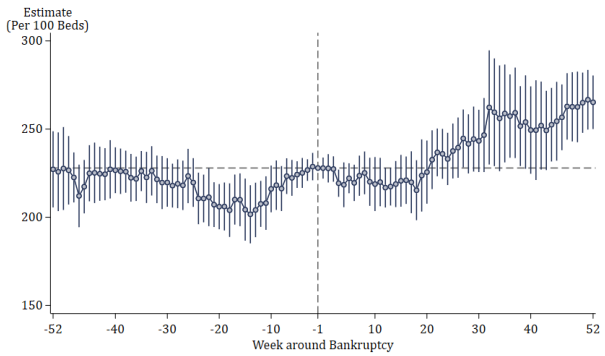
(d) $<$ 60 Days Tenure LPNs

Note. This figure examines staffing by workers of different experience levels. The left panel shows total weekly (per 100 beds) LPNs with at least 60 days of experience at the facility. The right panel shows total weekly (per 100 beds) LPNs with fewer than 60 days of experience at the facility. Standard errors clustered by nursing home chain, and 95% confidence intervals are shown.

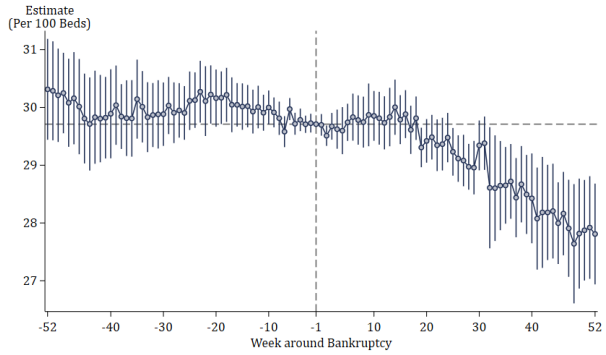
Figure C4: Dynamic Effects of Bankruptcy on Certified Nursing Assistant (CNA) Staffing Tenure



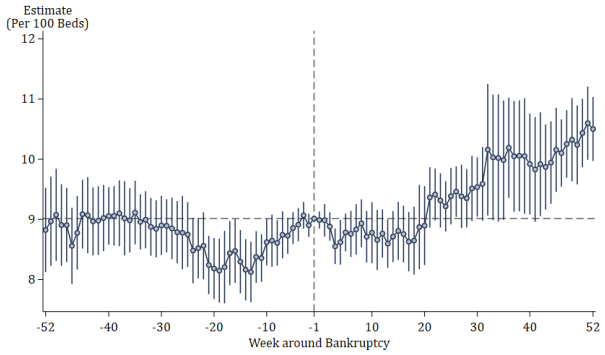
(a) ≥ 60 Days Tenure CNA Hours



(b) < 60 Days Tenure CNA Hours



(c) ≥ 60 Days Tenure CNAs



(d) < 60 Days Tenure CNAs

Note. This figure examines staffing by workers of different experience levels. The left panel shows total weekly (per 100 beds) CNAs with at least 60 days of experience at the facility. The right panel shows total weekly (per 100 beds) CNAs with fewer than 60 days of experience at the facility. Standard errors clustered by nursing home chain, and 95% confidence intervals are shown.

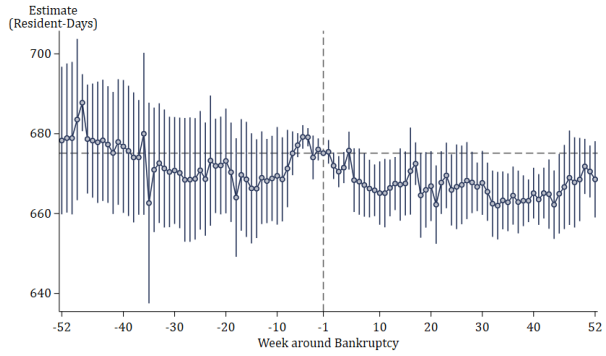
C.3 Staffing Levels and Wages

Table C1: The Effect of Bankruptcy on Nursing Staff Wages

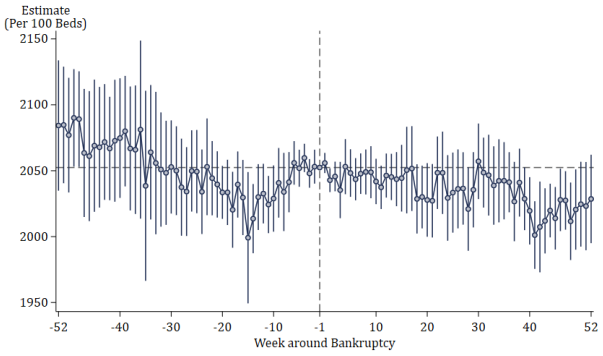
	All Nurses	RN	LPN	CNA
Bankrupt	0.024***	0.019**	0.018**	0.023**
	(0.007)	(0.008)	(0.009)	(0.009)
FE: Facility	Yes	Yes	Yes	Yes
FE: Year × Cohort	Yes	Yes	Yes	Yes
Observations	26,251	26,251	26,251	26,251
R^2	0.86	0.76	0.83	0.85
Mean	2.98	3.52	3.26	2.67
Std. Dev	0.22	0.22	0.21	0.22

Note. The dependent variables are the natural log of average hourly wages by nursing staff type. Each observation is an annual filing in the Healthcare Cost Report Information System (HCRIS). The specification contains facility fixed effects as well as fiscal year by match cohort fixed effects. We drop the filing covering the fiscal year of the bankruptcy filing, but the result is robust to including the fiscal year of bankruptcy as either a treatment or control observation. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

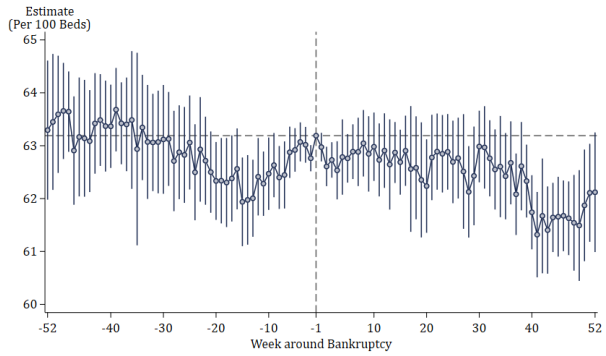
Figure C5: Event Studies of Occupancy, Staffing Levels, and Skill Mix



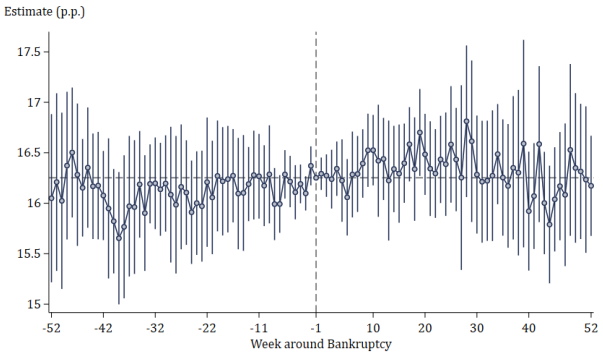
(a) Resident-Days



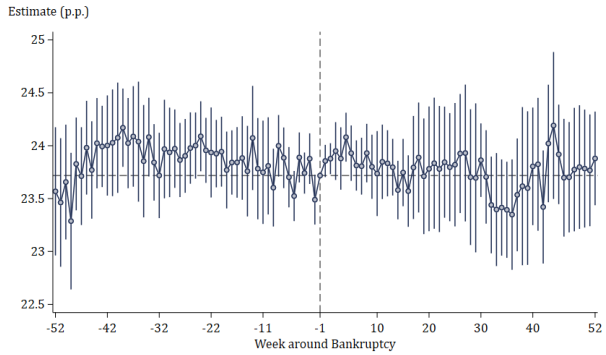
(b) Hours per 100 Beds



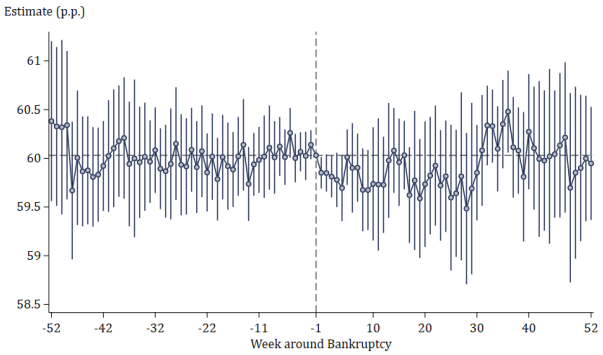
(c) Workers per 100 Beds



(d) RN Share



(e) LPN Share



(f) CNA Share

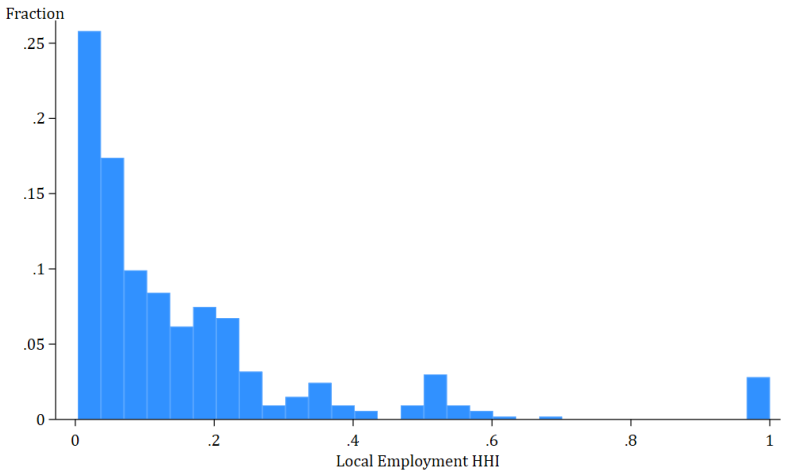
Note. We estimate the dynamic difference-in-differences specification (2) to calculate bankruptcy treatment effects in each week around the filing date. In each panel of this figure, we plot the treatment-effect estimates (on the y axis) for each week (on the x axis) around the bankruptcy filing. In panel (a), the dependent variable is the number of days each resident spends at the facility in week w, summed across residents. In panel (b), the dependent variable is the number of hours worked by any staff in week w per 100 beds. In panel (c), the dependent variable is the number of workers in week w per 100 beds. In panels (d), (e), and (f), the dependent variables are the share of hours in week w worked by RNs, LPNs, and CNAs, respectively. We calculate standard errors for each treatment-effect estimate, clustering by nursing home chain. The vertical line covering each estimate displays a 95% confidence interval. The vertical dashed line marks one week before the bankruptcy filing. See Table 2 for point estimates.

C.4 Heterogeneity by Local Labor Market Concentration

In this section, we test whether bankruptcy-induced staff turnover differs with local competition for nursing staff. We measure local labor market concentration using a Herfindahl Hirschman Index (HHI) based on nursing home employment in each county. Specifically, we obtain average daily staffing hours for every US nursing home, then calculate the sum of squared facility employment shares for each county-year. (In a given year, a facility's employment share is the share of total county-wide nursing home hours employed by that facility). We measure each nursing home's HHI in the year before the bankruptcy filing. That is, we use a time-invariant measure of market concentration for each facility in the regressions.

Figure C6 presents the distribution of labor HHIs for bankruptcy-filing facilities in the year prior to bankruptcy. An HHI value closer to 1 indicates a more concentrated labor market (fewer nursing home employers). The majority of facilities face highly competitive local labor markets; the median and 75th percentile of HHI are 0.09 and 0.20, respectively.

Figure C6: Employment HHI Distribution of Nursing Homes in Year Before Bankruptcy



Note. This shows the distribution of nursing home employment HHIs across facilities in the year before bankruptcy. HHI is calculated at the county-year level based on employment shares of each nursing home.

We define $\widetilde{HHI}_f = HHI_f/\sigma$, where σ is the standard deviation of HHI across facilities in the year before bankruptcy and is approximately 0.20 in our sample. Tables C2 and C3 present the estimates from the following dynamic specification, a "triple-difference" analogue

of Equation (1) in the main text:

$$
\begin{aligned}
y_{f,w,c} = {} & \delta B_f \mathbf{1}\{w < T_c - 52\} + \delta^H B_f \mathbf{1}\{w < T_c - 52\} \times \widetilde{HHI}_f \\
& + \theta_1 B_f \mathbf{1}\{T_c \leq w \leq T_c + 52\} + \theta_1^H B_f \mathbf{1}\{T_c \leq w \leq T_c + 52\} \times \widetilde{HHI}_f \\
& + \theta_2 B_f \mathbf{1}\{w > T_c + 52\} + \theta_2^H B_f \mathbf{1}\{w > T_c + 52\} \times \widetilde{HHI}_f \\
& + \alpha_{w,c} + \rho_f + \epsilon_{f,w,c}
\end{aligned} \tag{13}
$$

where the notation follows that of Equation (1). The estimates show that the turnover and tenure effects are significantly smaller in more concentrated local labor markets. In other words, the losses of high-tenure workers and shift towards new hires are substantially larger in more competitive local labor markets.

Table C2: The Effect of Bankruptcy on Nursing Staff Turnover by Local Labor Market Concentration

	All		RN		LPN		CNA	
	New Hires	Exits	New Hires	Exits	New Hires	Exits	New Hires	Exits
$0 \leq t \leq 52$	0.225***	0.222***	0.021**	0.027***	0.058***	0.067***	0.149***	0.125***
	(0.047)	(0.040)	(0.010)	(0.008)	(0.009)	(0.010)	(0.034)	(0.031)
$(0 \leq t \leq 52) \times \widetilde{HHI}$	-0.135***	-0.096	-0.015*	-0.004	-0.028***	-0.027***	-0.090***	-0.058
	(0.046)	(0.060)	(0.008)	(0.013)	(0.007)	(0.007)	(0.034)	(0.040)
$t \geq 53$	0.174***	0.178***	-0.003	0.022***	0.066***	0.060***	0.117***	0.096***
	(0.048)	(0.034)	(0.009)	(0.007)	(0.012)	(0.014)	(0.032)	(0.025)
$(t \geq 53) \times \widetilde{HHI}$	-0.038	-0.067	0.001	-0.009	-0.028***	-0.026**	-0.019	-0.030
	(0.050)	(0.046)	(0.009)	(0.007)	(0.010)	(0.011)	(0.035)	(0.031)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.37	0.42	0.27	0.28	0.30	0.32	0.34	0.38
Mean	1.35	1.42	0.19	0.21	0.26	0.28	0.89	0.92
Observations	459,804	459,804	459,804	459,804	459,804	459,804	459,804	459,804

Note. This table presents the estimates of Equation (13). For each facility, we calculate the nursing home employment HHI of its county in the year prior to bankruptcy. The dependent variable New Hires represents the number of new workers in a facility-week per 100 beds. The dependent variable Exits represents the number of exiting workers in a facility-week per 100 beds. The results are shown for all nursing staff, RNs, LPNs, and CNAs, respectively. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Table C3: The Effect of Bankruptcy on the Tenure of Nursing Staff

	$\geq$ 60 Days Tenure			$<$ 60 Days Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
$0 \leq t \leq 52$	-80.907***	-3.322***	-2.348***	48.775***	3.322***	1.567***
	(13.869)	(0.478)	(0.467)	(9.654)	(0.478)	(0.357)
$(0 \leq t \leq 52) \times \widetilde{HHI}$	45.587***	1.613***	1.180***	-24.817***	-1.613***	-0.802**
	(10.716)	(0.437)	(0.382)	(8.833)	(0.437)	(0.355)
$t \geq 53$	-121.070***	-3.734***	-3.683***	48.285***	3.734***	1.657***
	(15.475)	(0.706)	(0.529)	(12.332)	(0.706)	(0.485)
$(t \geq 53) \times \widetilde{HHI}$	30.590**	0.611	0.651	-1.095	-0.611	0.062
	(12.766)	(0.529)	(0.426)	(12.423)	(0.529)	(0.524)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.53	0.87	0.58	0.53	0.63
Mean	1,692.67	81.66	49.03	363.12	18.34	14.36
Observations	459,804	459,804	459,804	459,804	459,804	459,804

Note. This table presents the estimates of Equation (13). For each facility, we calculate the nursing home employment HHI of its county in the year prior to bankruptcy. This table examines staffing by workers of different experience levels, measured in days. The dependent variable Hours represents weekly hours per 100 beds. The dependent variable Hour Share represents share of total weekly hours. The dependent variable Employees represents number of working employees per 100 beds. The results are shown for all nursing staff. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. Tenure by hour share is illustrated in Figure 3. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

C.5 Alternative Definitions of Low Tenure

This section demonstrates the robustness of our tenure result to alternative tenure definitions. The main text presents results in which low-tenure staff are defined as those that have worked fewer than 60 days at the facility, as this is approximately the 25th percentile of employee tenure of 59 days. Table C4 shows the results hold with alternative tenure cutoffs of 30 days and 90 days.

Table C4: Robustness: The Effect of Bankruptcy on the Tenure of Nursing Staff

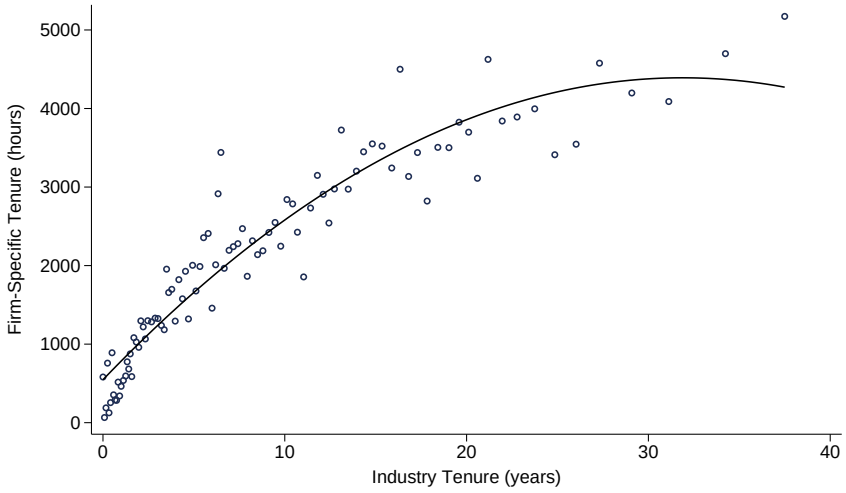
	$\geq$ 30 Days Tenure			$<$ 30 Days Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
$0 \leq t \leq 52$	-31.974***	-1.276***	-1.070***	15.524***	1.276***	0.584***
	(12.237)	(0.261)	(0.388)	(5.496)	(0.261)	(0.222)
$t \geq 53$	-70.568***	-1.827***	-2.338***	24.037***	1.827***	0.930***
	(10.523)	(0.400)	(0.314)	(8.531)	(0.400)	(0.349)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.89	0.42	0.90	0.50	0.42	0.56
Mean	1,865.52	90.13	55.07	192.09	9.87	8.36
Observations	459,804	459,804	459,804	459,804	459,804	459,804

	$\geq$ 90 Days Tenure			$<$ 90 Days Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
$0 \leq t \leq 52$	-77.207***	-3.513***	-2.305***	58.952***	3.513***	1.724***
	(19.179)	(0.834)	(0.618)	(13.385)	(0.834)	(0.432)
$t \geq 53$	-142.511***	-5.586***	-4.559***	92.076***	5.586***	3.053***
	(21.475)	(1.328)	(0.788)	(26.374)	(1.328)	(0.951)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.84	0.70	0.85	0.70	0.70	0.72
Mean	1,504.03	72.46	42.99	551.90	27.54	20.38
Observations	459,804	459,804	459,804	459,804	459,804	459,804

Note. This table examines staffing by workers of different experience levels, measured in days. The dependent variable Hours represents weekly hours per 100 beds. The dependent variable Hour Share represents share of total weekly hours. The dependent variable Employees represents number of working employees per 100 beds. The results are shown for all nursing staff. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

C.6 Correlation between Firm-Specific and Industry Tenure

Figure C7: Firm-Specific and Industry Tenure for CNAs in Illinois (from Gandhi, Olenski, Ruffini, and Shen (2023)



Note. This figure demonstrates the relationship between firm-specific tenure in PBJ and self-certified lifetime experience of CNAs. The data are from 2022. The CNA experience data were collected for an Medicaid reimbursement reform in Illinois intended to incentivize facilities to employ experienced CNAs.

D Facility Closures and Changes in Ownership

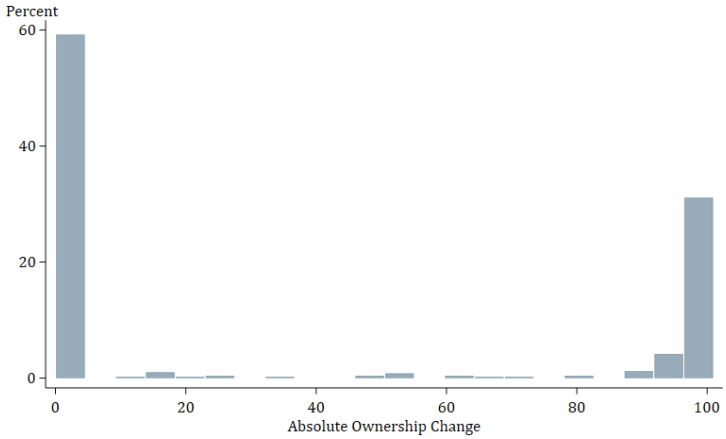
This paper studies the effects of bankruptcy on employees and patients. In doing so we focus on Chapter 11 reorganizations, during which debtors continue to operate while bankruptcy proceedings take place. However, it is possible for firms to shut down as a result of the restructuring even after filing for Chapter 11.

While one way to detect closures might be to observe conversions to Chaper 7 liquidation, this method might underestimate closures since liquidations can also occur in Chapter 11. Instead, we detect closures by observing attrition from the operations data. Since not all facilities were required to submit staffing data in 2020Q1 due to COVID-19, we count attrition up to 2019. We find that a small percentage of facilities close during the sample period. Specifically, 6% of facilities (34 total) have Payroll Based Journal (PBJ) staffing data that end sometime before the last week of 2019.

Most commonly, providers continue operating after filing for Chapter 11 bankruptcy. However, we do observe a small increase in ownership changes after bankruptcy. We investigate this by obtaining the ownership files from CMS, which track the owners of each facility over time. Figure D1 provides the empirical distribution of ownership changes during the sample period. The majority of facilities do not change ownership at all, and close to 30% of facilities undergo a complete (100%) change in ownership.

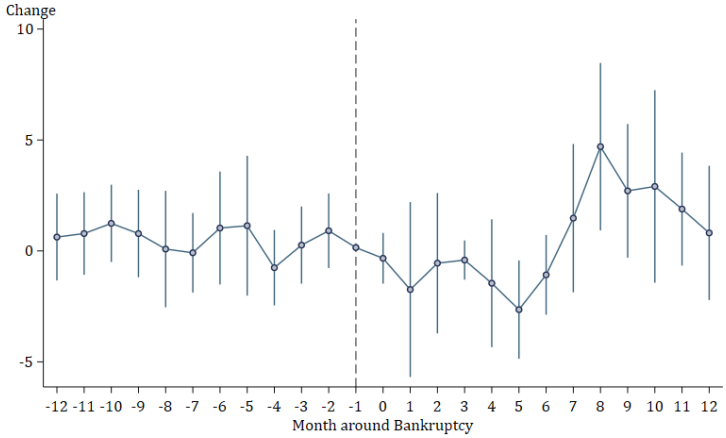
We formally investigate ownership changes around bankruptcy through a difference-in-differences analysis of monthly percent ownership changes at the facility level. The dynamic event study of Figure D2 shows a delayed increase in ownership changes, with a noticeable five percentage point average effect at eight months post-filing. This delay seems reasonable given that bankruptcy proceedings take time.

Figure D1: Empirical Ownership Change Distribution



Note. This figure displays the distribution of absolute ownership changes using a histogram.

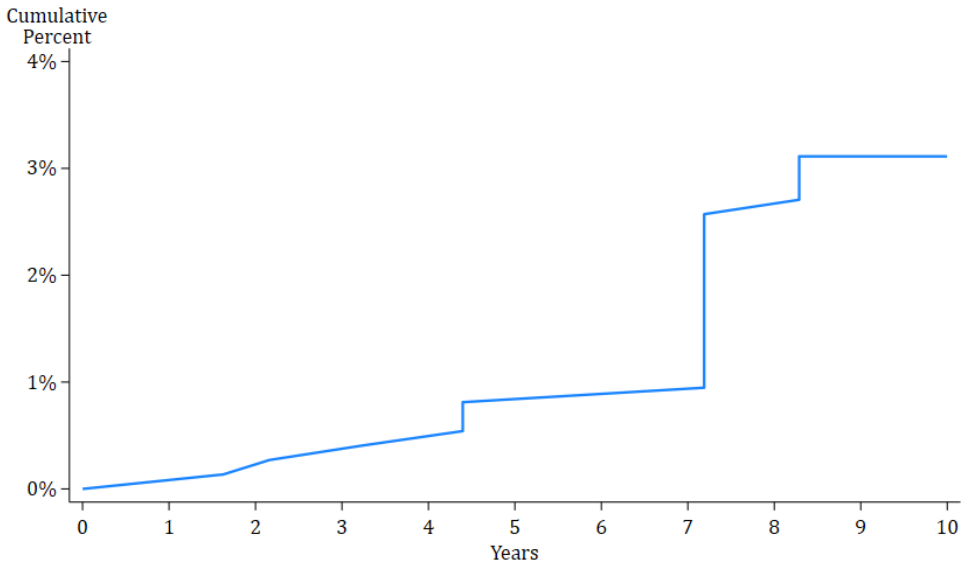
Figure D2: Dynamic Estimates of Ownership Change around Bankruptcy



Note. This figure shows how ownership changes around a bankruptcy filing.

D.1 Private Equity Ownership of Bankrupt Facilities

Figure D3: Time Between Bankruptcy and Most Recent Private Equity Acquisition

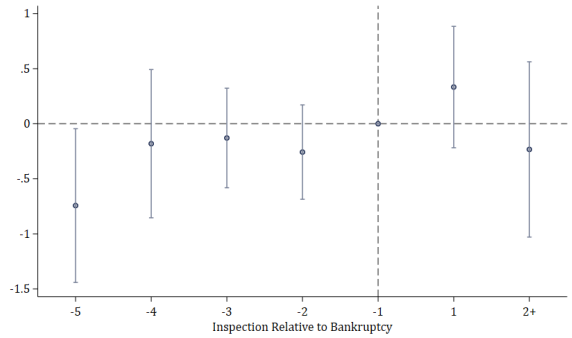


Note. This figure shows the CDF of days since leveraged buyout (LBO) for bankruptcy-filing facilities in the sample, for LBOs within ten years (3,650 days) of the bankruptcy date. Data on private equity ownership of nursing homes is from Gandhi, Song, and Upadrashta (2022).

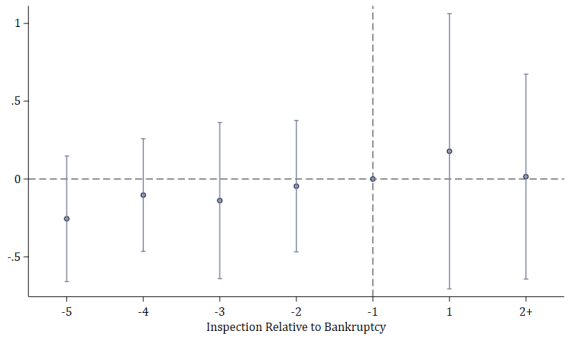
E Supplemental Health Inspections Analysis

E.1 Event Studies

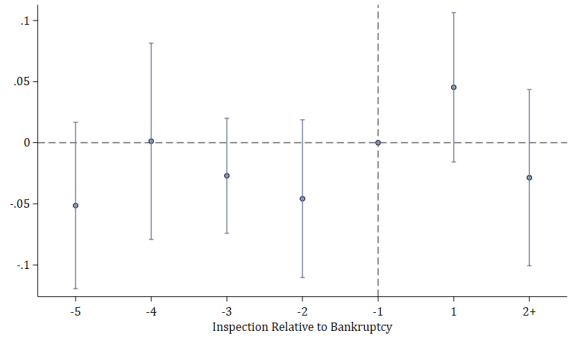
Figure E1: Provider Bankruptcy and Performance on Health Inspections: Event Studies



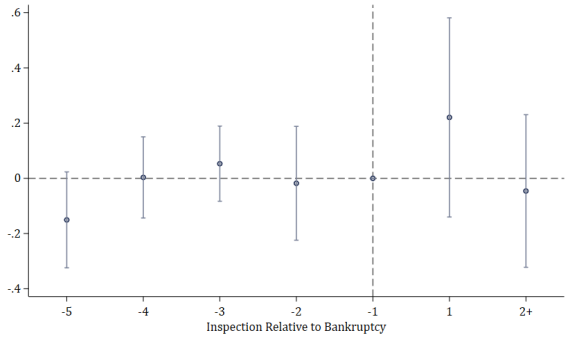
(a) Standard Deficiencies



(b) Complaint Deficiencies



(c) Nursing Services Violations



(d) Quality of Care Violations

Note. This figure presents the dynamic diff-in-diff estimates corresponding to Equation (3) and Table 6 in the main text. Each observation is a facility observed during the τth inspection relative to the bankruptcy filing date. The dependent variables are the number of Standard deficiencies, the number of Complaint deficiencies, the number of deficiencies that fall under the Nursing Services category, and the number of deficiencies that fall under the Quality of Care category. Standard deficiencies are violations incurred during unannounced health inspector visits that occur on an annual basis. Complaint deficiencies are violations that arise from filed complaints. Standard errors are clustered by nursing home chain and 95% confidence intervals are shown.

E.2 Severity and Scope

Table E1: Provider Bankruptcy and the Scope and Severity of Health Inspection Citations

Panel A. Scope of Deficiencies

	Isolated	Pattern	Widespread
$\tau = 1$	0.960**	0.082	0.011
	(0.432)	(0.200)	(0.121)
$\tau \geq 2$	0.299	-0.151	0.060
	(0.393)	(0.232)	(0.128)
FE: Facility	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes
Observations	33,052	33,052	33,052
R^2	0.58	0.57	0.43
Mean	5.41	2.33	0.67
Std. Dev	5.12	3.06	1.22

Panel B. Severity of Deficiencies

	Potential for Minimal Harm	Potential for Actual Harm	Actual Harm or Immediate Jeopardy
$\tau = 1$	-0.001	1.015*	0.040
	(0.030)	(0.568)	(0.086)
$\tau \geq 2$	-0.051	0.296	-0.038
	(0.046)	(0.589)	(0.086)
FE: Facility	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes
Observations	33,052	33,052	33,052
R^2	0.45	0.57	0.36
Mean	0.35	7.60	0.47
Std. Dev	0.78	6.51	1.19

Note. This table studies the varying levels of scope and severity of deficiencies according to CMS guidelines. Scope includes isolated, pattern, and widespread deficiencies. Severity includes deficiencies with potential for minimal harm, deficiencies with potential for actual harm, and deficiencies that indicate actual harm or immediate jeopardy. The dependent variable is measured as the number of deficiencies in each column. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

E.3 Decomposing Deficiencies Related to Nursing Services

Table E2: Provider Bankruptcy and Citations Related to Nursing Services

	Insufficient Staffing	Incompetent Staffing	Violating RN Minimums	Missing CNA Performance Review or In-Service Training	Failure to Post Staffing and Census
$\tau = 1$	0.026*	0.004	0.001	0.016**	0.034***
	(0.015)	(0.016)	(0.008)	(0.007)	(0.010)
$\tau \geq 2$	0.002	-0.025*	0.003	0.009	0.007
	(0.014)	(0.015)	(0.007)	(0.010)	(0.010)
FE: Facility	Yes	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes	Yes
Observations	33,052	33,052	33,052	33,052	33,052
R^2	0.38	0.37	0.35	0.33	0.29
Mean	0.06	0.07	0.01	0.02	0.04
Std. Dev	0.27	0.28	0.11	0.14	0.20

Note. This table investigates each individual tag that falls under the Nursing Services category. From left to right, these tags are: F725, F726, F727, F730, and F732. We exclude deficiency tags F728, F729, and F731 with citations that occurred less than 0.5% of the time (overall sample mean ≈0.00).The dependent variable is measured as the number of deficiencies in each column. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

E.4 Decomposing Deficiencies Related to Quality of Care

Table E3: Implications of Provider Bankruptcy for Patient Health and Safety: Quality of Care Tags

	Inadequate Care	Lack of Vision/Hearing Services Assistance	Poor Pressure Ulcer Prevention	Insufficient Foot Care	Failure to Prevent Mobility Decline
$\tau = 1$	0.043	0.009	0.036	-0.001	0.005
	(0.033)	(0.008)	(0.030)	(0.012)	(0.011)
$\tau \geq 2$	0.015	0.001	-0.045**	-0.002	-0.009
	(0.035)	(0.008)	(0.022)	(0.012)	(0.014)
FE: Facility	Yes	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes	Yes
Observations	33,052	33,052	33,052	33,052	33,052
R^2	0.43	0.31	0.38	0.37	0.33
Mean	0.40	0.01	0.21	0.08	0.07
Std. Dev	0.65	0.12	0.46	0.28	0.27

	Inadequate Accident Prevention	Inadequate Continence Care	Poor Ostomy Care	Insufficient Nutrition Support	Unnecessary Tube Feeding
$\tau = 1$	0.063	0.009	0.002	0.022	0.030*
	(0.043)	(0.014)	(0.010)	(0.017)	(0.018)
$\tau \geq 2$	0.022	-0.020	0.003	-0.004	0.012
	(0.033)	(0.021)	(0.014)	(0.019)	(0.013)
FE: Facility	Yes	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes	Yes
Observations	33,052	33,052	33,052	33,052	33,052
R^2	0.42	0.36	0.37	0.34	0.34
Mean	0.50	0.17	0.08	0.11	0.06
Std. Dev	0.72	0.40	0.28	0.35	0.25

	Unsafe Parenteral Fluid Administration	Insufficient Respiratory Care	Inadequate Prosthesis Care	Insufficient Pain Management Services	Poor Dialysis Care	Improper Bedrail Use
$\tau = 1$	0.013	0.030	-0.001	0.002	0.007	0.077**
	(0.015)	(0.025)	(0.010)	(0.047)	(0.056)	(0.038)
$\tau \geq 2$	-0.011	-0.006	-0.008	-0.046	-0.052	0.022
	(0.012)	(0.014)	(0.012)	(0.033)	(0.038)	(0.023)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Observations	33,052	33,052	33,052	33,052	33,052	33,052
R^2	0.37	0.37	0.37	0.43	0.43	0.43
Mean	0.08	0.11	0.08	0.33	0.33	0.39
Std. Dev	0.29	0.33	0.28	0.59	0.59	0.64

Note. This table investigates each individual tag that falls under the Quality of Care category. The dependent variable is measured as the number of deficiencies in each column. Standard errors are provided in parentheses and are clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

F Robustness to Additional Match Criteria

This section demonstrates the robustness of the main results that use the matched difference-in-differences design to additional match criteria. Specifically, in addition to exact matching on ten deciles of Medicare share, occupancy rate, and bed count, we also exact match on for-profit status. Since we coarse exact match to controls without replacement, the additional match restriction reduces the matched sample size. Ultimately, the findings are qualitatively unchanged.

Table F1: Balance Table (Alternative Match)

	(1) Treated Facilities	(2) Control Facilities	(3) |Diff|/SD
Match Variables			
Percent Medicare	14.34	14.22	0.01
	(9.80)	(10.76)	
Occupancy Rate	79.24	78.75	0.03
	(14.76)	(14.72)	
Certified Beds	122.43	124.85	0.05
	(39.42)	(48.78)	
Staffing Characteristics (Not Matched On)			
New Hires	1.45	1.28	0.10*
	(1.89)	(1.78)	
Separations	1.31	1.23	0.03
	(1.56)	(2.55)	
Staffing Hours	1975.87	1982.99	0.01
	(503.03)	(623.65)	
$\geq$ 60 Days Tenure Hours	1374.22	1365.80	0.01
	(683.80)	(770.49)	
$<$ 60 Days Tenure Hours	601.65	617.20	0.02
	(546.79)	(624.81)	
$\geq$ 60 Days Tenure Hour Share	68.46	67.37	0.04
	(28.57)	(30.70)	
$<$ 60 Days Tenure Hour Share	31.54	32.63	0.04
	(28.57)	(30.70)	
N	465	2,110	2,575

Note. We match each bankrupt (treated) facility to a group of facilities that never file for bankruptcy (controls). This table compares treated facilities to control facilities measured 52 weeks before bankruptcy. For each variable, we present its mean for treated and control facilities in columns (1) and (2), respectively. We present standard deviations in parentheses. In column (3), we present the absolute value of the difference between the means in columns (1) and (2), normalized by the control-group standard deviation. We indicate the statistical significance of this difference at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Table F2: The Effect of Bankruptcy on Nursing Staff Turnover (Alternative Match)

	All		RN		LPN		CNA	
	New Hires	Exits	New Hires	Exits	New Hires	Exits	New Hires	Exits
$0 \leq t \leq 52$	0.114***	0.147***	0.011	0.022***	0.040***	0.046***	0.066**	0.079***
	(0.043)	(0.035)	(0.007)	(0.006)	(0.008)	(0.008)	(0.032)	(0.025)
$t \geq 53$	0.152**	0.122***	-0.002	0.012	0.049***	0.038***	0.103**	0.073**
	(0.064)	(0.041)	(0.012)	(0.010)	(0.010)	(0.009)	(0.044)	(0.030)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.36	0.42	0.28	0.29	0.29	0.31	0.33	0.37
Mean	1.34	1.41	0.19	0.21	0.27	0.28	0.87	0.90
Observations	430,722	430,722	430,722	430,722	430,722	430,722	430,722	430,722

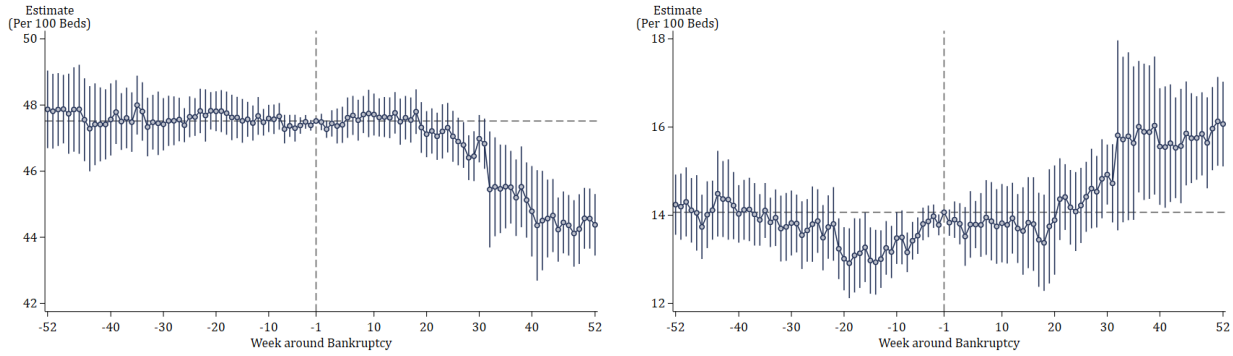
Note. The dependent variable New Hires represents the number of new workers in a facility-week per 100 beds. The dependent variable Exits represents the number of exiting workers in a facility-week per 100 beds. The results are shown for all nursing staff, RNs, LPNs, and CNAs, respectively. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Table F3: The Effect of Bankruptcy on the Tenure of Nursing Staff (Alternative Match)

	$\geq$ 60 Days Tenure			$<$ 60 Days Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
$0 \leq t \leq 52$	-38.083***	-1.876***	-1.120***	28.599***	1.876***	0.922***
	(14.611)	(0.528)	(0.431)	(8.978)	(0.528)	(0.308)
$t \geq 53$	-95.952***	-3.330***	-3.056***	50.112***	3.330***	1.812***
	(14.197)	(0.729)	(0.453)	(15.747)	(0.729)	(0.651)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.53	0.87	0.58	0.53	0.63
Mean	1,648.29	81.50	47.52	359.13	18.50	14.07
Observations	430,722	430,722	430,722	430,722	430,722	430,722

Note. This table examines staffing by workers of different experience levels, measured in days. The dependent variable Hours represents weekly hours per 100 beds. The dependent variable Hour Share represents share of total weekly hours. The dependent variable Employees represents number of working employees per 100 beds. The results are shown for all nursing staff. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. Tenure by hour share is illustrated in Figure 3. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Figure F1: Dynamic Effects of Bankruptcy on Nursing Staff Tenure (Alternative Match)



(a) $\geq$ 60 Days Tenure Workers

(b) $<$ 60 Days Tenure Workers

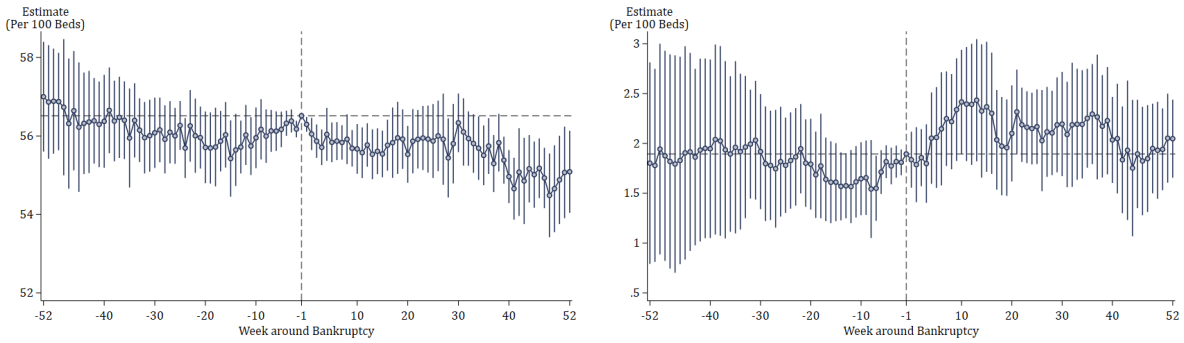
Note. This figure examines staffing by workers of different experience levels. The left panel shows the share of weekly staffing hours provided by workers with at least 60 days of experience at the facility. The right panel shows the share of weekly staffing hours with fewer than 60 days of experience at the facility. Standard errors are clustered by nursing home chain, and 95% confidence intervals are shown. Table 4 contains the coinciding point estimates. Appendix C.2 contains the event studies for all tenure variables and for each nursing staff role.

Table F4: Staffing Responses to Bankruptcy by Employment Contract (Alternative Match)

	Wage Workers			Contract Workers		
	Hours	Hour Share	Employees	Hours	Hour Share	Employees
$0 \leq t \leq 52$	-20.523*	-0.683**	-0.556**	7.356*	0.732***	0.307
	(10.476)	(0.277)	(0.278)	(4.170)	(0.205)	(0.191)
$t \geq 53$	-57.289***	-1.167**	-1.667***	12.286**	1.052***	0.482***
	(13.670)	(0.518)	(0.416)	(4.811)	(0.310)	(0.152)
FE: Facility	Yes	Yes	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.86	0.57	0.88	0.66	0.57	0.66
Mean	1,855.88	92.47	56.52	40.23	2.33	1.89
Observations	483,032	483,032	483,032	483,032	483,032	483,032

Note. This table examines staffing by workers of different employment contracts. Each observation is a facility-week. Standard errors are provided in parentheses and are clustered by nursing home chain. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Figure 4 for event studies.

Figure F2: Staffing Responses to Bankruptcy by Employment Contract (Alternative Match)



(a) Wage Workers

(b) Contract Workers

Note. This figure examines staffing by workers of different employment contracts. The left panel shows total weekly hours (per 100 beds) supplied by wage nursing staff. The right panel shows total weekly hours (per 100 beds) supplied by contract nursing staff. Standard errors are clustered by chain, and 95% confidence intervals are shown. See Table 5 for point estimates.

Table F5: Performance on Health Inspections After Bankruptcy (Alternative Match)

	Standard Deficiencies	Complaint Deficiencies	Nursing Services Violations	Quality of Care Violations
$\tau = 1$	0.605	0.211	0.072*	0.209
	(0.457)	(0.257)	(0.040)	(0.150)
$\tau \geq 2$	0.131	0.091	-0.011	0.007
	(0.548)	(0.261)	(0.030)	(0.140)
FE: Facility	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	Yes	Yes	Yes	Yes
Observations	31,006	31,006	31,006	31,006
R^2	0.55	0.48	0.39	0.54
Mean	6.54	2.10	0.19	1.74
Std. Dev	5.37	3.78	0.51	1.95

Note. Each observation is a facility observed during the τth inspection relative to the bankruptcy filing date. The dependent variables are the number of Standard deficiencies, the number of Complaint deficiencies, the number of deficiencies that fall under the Nursing Services category, and the number of deficiencies that fall under the Quality of Care category. Standard deficiencies are violations incurred during unannounced health inspector visits that occur on an annual basis. Complaint deficiencies are violations that arise from filed complaints. Standard errors are provided in parentheses and are clustered by nursing home chain. Event studies are provided in Figure E1. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

G Supplemental Health Outcomes Analysis

G.1 Demand Estimates

Table G1: Discrete-Choice Distance Model of Patients' Facility Choice

	Admission
Miles to Provider	-0.46
	(0.00025)
(Miles to Provider)^2	0.0087
	(0.000014)
N	722054502

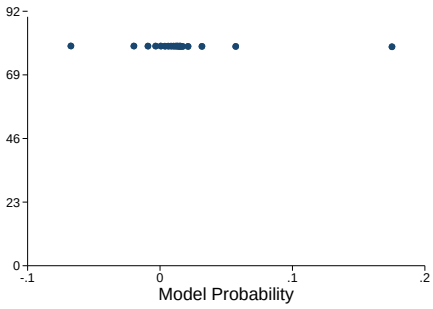
Note. We estimate equation (4) by maximum likelihood. This table presents our estimates of α_1, α_2 in the first and second rows, respectively. We present standard errors in parentheses.

G.2 Patient Characteristics and the Instrument, with Zip-Level Fixed Effects

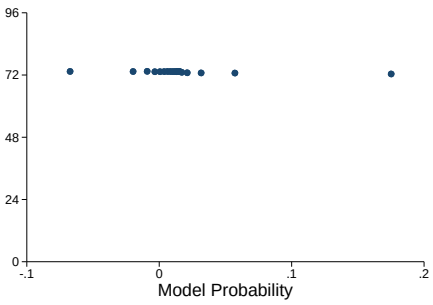
While the exclusion restriction is fundamentally untestable, Figure G1 provides some suggestive evidence in showing that our instrument is not strongly correlated with patients' health and demographic characteristics.

Figure G1: Patient Characteristics and the Instrument

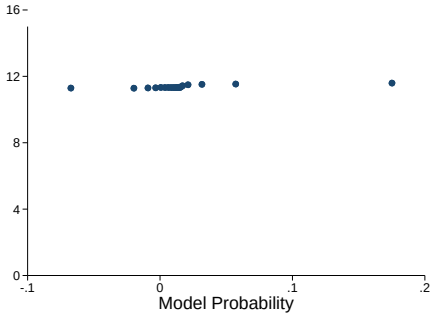
(a) Patient Age



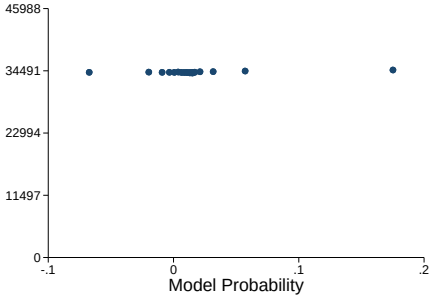
(b) Population that is White (%)



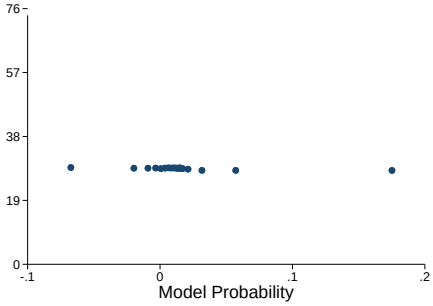
(c) Count of Chronic Conditions



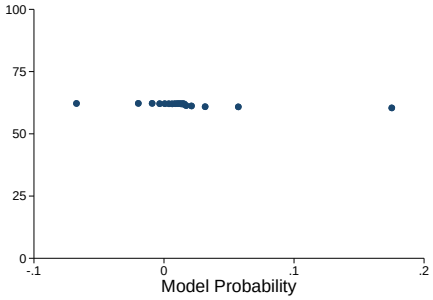
(d) Median Income ($)



(e) Dual Eligibles (%)



(f) Female Patients (%)



Note. Binscatters contain fixed effects for a beneficiaries ZIP code. The population that is white and median income are derived from the Ammerican Community Survey.

G.3 Alternative Assessments

Our primary health outcomes analysis considers 30-day resident assessments. This the third of five Medicare-mandated assessments and was chosen to balance greater sample size for earlier assessments against patients' greater exposure to the facility in later assessments. Table G2 presents our estimates when using 5, 14, 60, and 90 day assessments. The estimates are quite consistent with what we find in Table 7 Panel (B).

Two key patterns stand out. The first is that residents have lower ADL scores—indicating they receive less assistance—even at their 5-day assessment. This strongly suggests that the increase in patients' independence after the facility files for bankruptcy does not reflect a sharp improvement in care. If it did, it would necessarily imply that bankrupt facilities dramatically improve patients' independence within just a few days. More plausibly, these estimates are consistent with patients' apparent independence simply reflecting the inability for staff to provide sufficient assistance.

The second pattern that stands out is that the effect on catheterization is both statistically significant and larger in magnitude for 60 and 90 days surveys. This may reflect that the small fraction of patients eligible for 60 or 90 days of Medicare-covered skilled nursing care are highly selected in health characteristics towards being more eligible for discretionary catheterization. Likewise, it could be that the nature of care for patients in their 60th or 90th day differs substantially from patients in their first 30 days.

Table G2: Effect of Bankruptcy in Alternative Assessments

	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
5-day Assessment					
Bankrupt	0.0050	0.0041	0.0143***	0.0021	-0.5594***
	(0.0033)	(0.0043)	(0.0049)	(0.0037)	(0.0868)
N	8,586,841	8,590,390	8,581,452	8,588,691	8,583,788
R^2	0.334	0.168	0.104	0.087	0.226
Mean	0.018	0.119	0.156	0.106	8.15
SD	0.131	0.324	0.363	0.308	4.15
14-day Assessment					
Bankrupt	0.0082**	0.0009	0.0192***	0.0067	-0.4871***
	(0.0033)	(0.0048)	(0.0055)	(0.0041)	(0.0930)
N	5,899,925	5,901,426	5,899,635	5,901,039	5,900,836
R^2	0.279	0.177	0.096	0.091	0.220
Mean	0.018	0.125	0.147	0.085	7.70
SD	0.131	0.331	0.354	0.279	4.16
60-day Assessment					
Bankrupt	0.0132**	-0.0197	0.0384***	0.0239***	-0.3168*
	(0.0054)	(0.0126)	(0.0117)	(0.0082)	(0.1660)
N	898,770	898,955	898,736	898,886	898,880
R^2	0.251	0.235	0.123	0.134	0.229
Mean	0.026	0.166	0.146	0.081	7.86
SD	0.159	0.373	0.353	0.272	4.14
90-day Assessment					
Bankrupt	0.0006	-0.0075	0.0226	0.0241*	-0.3652
	(0.0081)	(0.0211)	(0.0183)	(0.0135)	(0.2697)
N	354,435	354,514	354,447	354,494	354,477
R^2	0.273	0.272	0.200	0.196	0.283
Mean	0.032	0.190	0.154	0.084	8.01
SD	0.177	0.392	0.361	0.278	4.22

Note. This table extends Table 7 Panel B, studying the same outcomes measured at different assessments conducted 5, 14, 60, or 90 days after the patient's admission to the facility. We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Table 7 for details.

G.4 Alternative Definitions of Recent Bankruptcy

Our primary health outcomes analysis defines a recent bankruptcy as one that occurred in the previous three years. Tables G3 and G4 present our estimates when defining a recent bankruptcy as one that occurred in the previous 1 and 5 years, respectively. Our findings are generally consistent with our estimates for 3 years. The notable exceptions are that both hospitalizations and pressure ulcers are not statistically significant when considering only one year after the bankruptcy filing. This may simply reflect that this definition results in a sample with far fewer treated individuals.

Table G3: Effect of Bankruptcy in Previous Year

Panel A: Claims-based Outcomes					
	Mortality	Hospitalization	Hospital Days	Fall-Based Hospitalization	Emergency Department
Bankrupt	-0.0047	0.0053	0.1345	0.0038	-0.0005
	(0.0052)	(0.0069)	(0.1200)	(0.0029)	(0.0073)
N	9,789,737	9,789,737	9,789,737	9,789,737	9,789,737
R^2	0.079	0.103	0.086	0.024	0.099
Mean	0.150	0.347	3.68	0.033	0.433
SD	0.358	0.476	8.83	0.18	0.496

Panel B: Assessment-based Outcomes					
	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
Bankrupt	0.0167***	-0.0009	0.0050	0.0039	-0.5608***
	(0.0043)	(0.0075)	(0.0087)	(0.0068)	(0.1184)
N	2,886,020	2,886,682	2,885,875	2,886,492	2,886,442
R^2	0.248	0.195	0.086	0.099	0.203
Mean	0.020	0.139	0.143	0.080	7.72
SD	0.139	0.346	0.35	0.272	4.12

Note. This table replicates Table 7 using a different definition of a recently-bankrupt facility: one that filed for bankruptcy within *one* year of the patient's admission to the facility. We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Table 7 for details.

Table G4: Effect of Bankruptcy in Previous 5 Years

Panel A: Claims-based Outcomes					
	Mortality	Hospitalization	Hospital Days	Fall-Based Hospitalization	Emergency Department
Bankrupt	-0.0050	0.0127**	0.2739***	0.0008	0.0083
	(0.0043)	(0.0059)	(0.1047)	(0.0024)	(0.0064)
N	9,884,891	9,884,891	9,884,891	9,884,891	9,884,891
R^2	0.079	0.103	0.086	0.024	0.099
Mean	0.151	0.347	3.68	0.034	0.433
SD	0.358	0.476	8.83	0.18	0.496

Panel B: Assessment-based Outcomes					
	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
Bankrupt	0.0076*	-0.0051	0.0191***	0.0027	-0.5060***
	(0.0046)	(0.0066)	(0.0069)	(0.0053)	(0.1132)
N	2,918,584	2,919,247	2,918,434	2,919,057	2,919,000
R^2	0.250	0.194	0.086	0.099	0.202
Mean	0.020	0.139	0.143	0.080	7.72
SD	0.139	0.346	0.35	0.272	4.12

Note. This table replicates Table 7 using a different definition of a recently-bankrupt facility: one that filed for bankruptcy within *five* years of the patient's admission to the facility. We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Table 7 for details.

G.5 Additional Health Outcomes

Table G5 presents estimates for additional MDS outcomes. Consistent with our null effect on chemical restraints, we do not find effects on either antipsychotic use or schizophrenia. When separating pressure ulcers into stage 1 and stage 2 pressure ulcers, we find clearer statistical significance for stage 1 ulcers. The effect size for stage 2 ulcers is also relatively large although our estimate is imprecise. We fine some evidence of weight loss, potentially suggesting that patients are receiving or consuming less food.

Notably, we observe an increase in BIMS scores. BIMS measures cognition through immediate recall, orientation, and short-term memory. These scores are recorded by staff and used to develop a residents' care plan. One possibility is that care improves or changes in a way that residents exhibit greater awareness during their BIMS tests. Other potential explanations include new staff unfamiliar with residents having different baseline expectations for cognition or inadequate documentation of deficiencies in cognition.

Finally, we observe increased use of antidepressants. The implications of this for patients is ambiguous and depends on whether their use is clinically appropriate and whether the need derives from worse mental health of patients after the bankruptcy.

Table G5: Effect of Bankruptcy on Additional Health Outcomes

			Pressure Ulcers		Weight Change	
	Antipsychotic	Schizophrenia	Stage 1	Stage 2	Gain	Loss
Bankrupt	-0.0026	0.0014	0.0196***	0.0096	-0.0006	0.0119*
	(0.0067)	(0.0011)	(0.0071)	(0.0065)	(0.0041)	(0.0062)
N	2,904,954	2,907,641	2,907,683	2,907,683	2,432,891	2,899,969
R^2	0.193	0.075	0.088	0.080	0.038	0.061
Mean	0.139	0.003	0.145	0.127	0.041	0.108
SD	0.346	0.053	0.352	0.333	0.198	0.31

	Falls	Pneumonia	UTIs	BIMS Score	Behavioral Issue	Antidepressant
Bankrupt	0.0020	-0.0016	-0.0073	0.2492***	0.0004	0.0186*
	(0.0061)	(0.0050)	(0.0076)	(0.0911)	(0.0006)	(0.0100)
N	2,907,002	2,907,021	2,907,683	2,627,632	2,907,683	2,905,321
R^2	0.041	0.107	0.104	0.294	0.028	0.258
Mean	0.090	0.060	0.146	11.6	0.001	0.437
SD	0.287	0.238	0.354	4.1	0.0341	0.496

Note. This table replicates Table 7 Panel B using different health outcomes. We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Table 7 for details.

G.6 Preference Over Log-Distance

In this section, we test the robustness of our findings to using an instrument constructed assuming preference in log-distance rather than a polynomial preference in distance. Formally this entails modifying equation (4)

$$u_{if} = \alpha \log\left(d(z(i), f)\right) + \epsilon_{if}. \tag{14}$$

Table G6 shows that our estimates are robust to using this alternative instrument.

Table G6: Health Impacts of Provider Bankruptcy

Panel A: Claims-based Outcomes

	Mortality	Hospitalization	Hospital Days	Fall-Based Hospitalization	Emergency Department
Bankrupt	-0.0015	0.0129**	0.2912***	0.0008	0.0107
	(0.0046)	(0.0064)	(0.1101)	(0.0025)	(0.0068)
N	9,853,046	9,853,046	9,853,046	9,853,046	9,853,046
R^2	0.079	0.103	0.086	0.024	0.099
Mean	0.151	0.347	3.68	0.034	0.433
SD	0.358	0.476	8.83	0.18	0.496

Panel B: Assessment-based Outcomes

	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
Bankrupt	0.0146***	-0.0038	0.0181**	0.0043	-0.5538***
	(0.0041)	(0.0071)	(0.0076)	(0.0056)	(0.1161)
N	2,907,000	2,907,663	2,906,850	2,907,473	2,907,416
R^2	0.250	0.194	0.086	0.099	0.203
Mean	0.020	0.139	0.143	0.080	7.72
SD	0.139	0.346	0.35	0.272	4.12

Note. Using 2SLS regressions (equation (8)) in a patient-level dataset, we estimate the effect of receiving care at a recently-bankrupt facility on patient health outcomes. We instrument for visiting a recently-bankrupt facility (one that filed within three years of the patient's admission) using w_i, a patient's model-implied likelihood of visiting a bankrupt facility given the patient's home ZIP code. In panel A, each column corresponds to a health outcome constructed using Medicare claims and enrollment records. These outcomes include indicators for a patient's mortality, hospitalization, fall-based hospitalization, and emergency-department visit within 90 days of the patient's admission to the facility. We also include the number of days the patients spends in the hospital within 90 days of admission to the facility. In panel B, each outcome is measured on a patient assessment conducted 30 days after admission to a facility. Four of the outcomes are indicators for: (i) the use of physical restraints, (ii) the use of chemical restraints, (iii) the patient suffering pressure ulcers (bed sores), or (iv) the use of a catheter. The final outcome is the patient's "Activities of Daily Living" (ADL) score. We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

G.7 Differential Distance Instrument

In this section, we test the robustness of our findings to using a simple "differential distance" instrument. For patient i living in ZIP code $z(i)$ admitted to nursing home $f(i)$ in month $t(i)$, we define differential distance D_i as the difference in log-distance between patient i's closest facility that recently filed for bankruptcy and i's closest facility that did not file for bankruptcy during our sample period.[24] We implement our instrumental variables approach via two-staged least squares:

$$B_{f(i)t(i)} = \gamma_1 D_i + \gamma_2 D_i^2 + \rho^B_{f(i)} + \eta^B_{z(i)} + \alpha^B_{t(i)} + X_i\varphi^B + \nu_i, \tag{15}$$

$$Y_i = \beta\widehat{B_{g(i)t(i)}} + \rho_{f(i)} + \alpha_{t(i)} + \eta_{z(i)} + X_i\varphi + \epsilon_i, \tag{16}$$

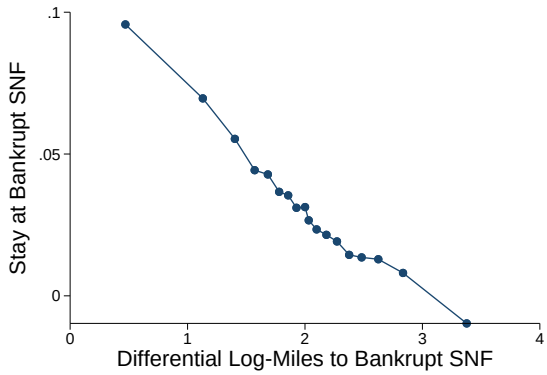
where $B_{f(i)t(i)}$ is an indicator for whether $f(i)$ filed for bankruptcy within three years prior to $t(i)$, and Y_i is a health outcome. The terms ρ, η, and α respectively represent facility, ZIP code, and time fixed effects. Finally, X_i contains a host of other health and demographic controls, including fixed-effects for age, race, gender, ESRD, dual eligibility, 22 distinct chronic conditions, and the primary diagnosis from their qualifying pre-admission hospital stay.

Figure G2 shows a strong relationship between differential distance and whether a patient receives care at a recently-bankrupt facility. Indeed, the distance instrument has a first-stage F-stat of 1295. Therefore, the validity of this approach relies on the assumption that the instruments D_i and D_i^2 are uncorrelated with the error term ϵ_i. Intuitively, what we require is that conditioning on our host of fixed effects and controls, differential distance does not correlate with health outcomes except through choice of facility. While the assumption is fundamentally untestable, we provide some suggestive evidence in Figure G3, which shows that the instrument is not substantially correlated with patient characteristics likely to influence health outcomes.

Table G7 presents our estimates. In general, they are consistent with our primary specification but substantially larger in magnitude. Our estimates are also statistically significant for three outcomes where they are not in our main specification: fall-based hospitalizations, catherizations, and chemical restraints. Notably, the point estimate for chemical restraints stands out in suggesting improvements in care.

[24] We follow convention by excluded cases with exceedingly differential distances. Specifically, we exclude differential distances above 50 miles, which is more than ten times the 4.8 miles that Gupta et al. (2024) finds the median patient travels.

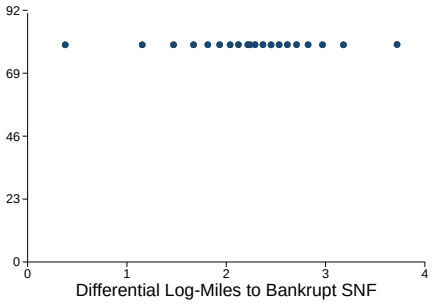
Figure G2: First Stage: Differential Distance



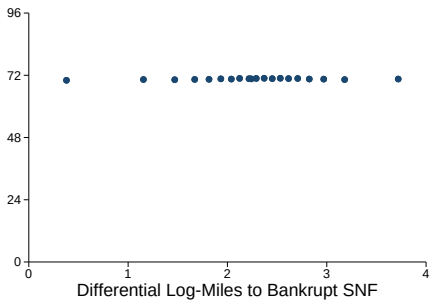
Note. This figure replicates Figure 5b, except that we use a different instrument to form bins: the difference in log-distance between patient i's closest facility that recently filed for bankruptcy and i's closest facility that did not file for bankruptcy during our sample period. See Figure 5b for details.

Figure G3: Patient Characteristics and Differential Distance, with Zip-Level Controls

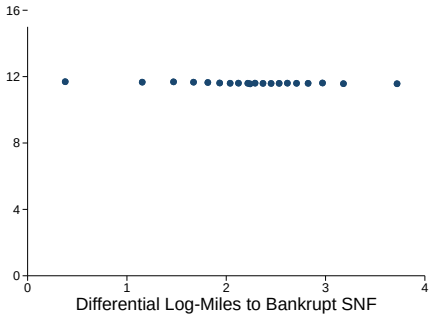
(a) Patient Age



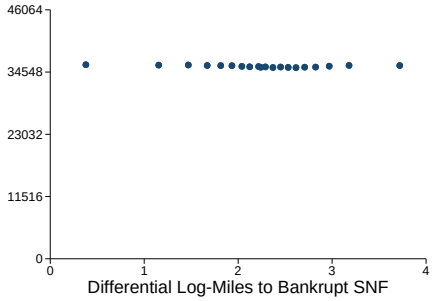
(b) Population that is White (%)



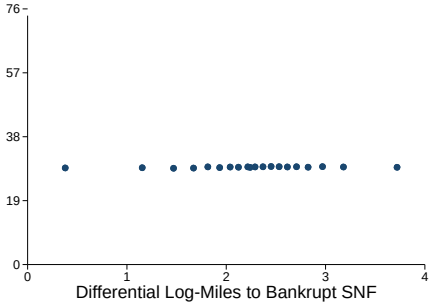
(c) Count of Chronic Conditions



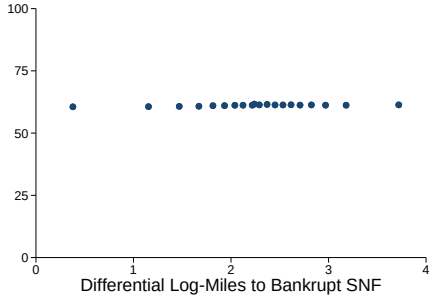
(d) Median Income ($)



(e) Dual Eligibles (%)



(f) Female Patients (%)



Note. Binscatters contain fixed effects for a beneficiaries ZIP code. The population that is white and median income are derived from the Ammerican Community Survey.

Table G7: Health Effects of Bankruptcy Using Differential Distance

Panel A: Claims-based Outcomes					
	Mortality	Hospitalization	Hospital Days	Fall-Based Hospitalization	Emergency Department
Bankrupt	0.0011	0.0718***	1.350***	0.0197***	0.0168
	(0.0080)	(0.0119)	(0.2312)	(0.0047)	(0.0127)
N	5,101,230	5,101,230	5,101,230	5,101,230	5,101,230
R^2	0.082	0.107	0.090	0.031	0.104
Mean	0.147	0.350	3.77	0.036	0.436
SD	0.354	0.477	8.98	0.185	0.496

Panel B: Assessment-based Outcomes					
	Restraints		Pressure Ulcers	Catheter	ADL Score
	Physical	Chemical			
Bankrupt	0.0307***	-0.0395***	0.1000***	0.0175*	-0.6633***
	(0.0115)	(0.0138)	(0.0163)	(0.0098)	(0.1978)
N	2,269,992	2,270,489	2,269,938	2,270,344	2,270,296
R^2	0.281	0.209	0.096	0.112	0.210
Mean	0.019	0.146	0.163	0.088	7.89
SD	0.138	0.353	0.369	0.284	4.03

Note. This table replicates Table 7 using a different instrument: the difference between (i) the logarithm of the distance between patient i and the nearest recently-bankrupt facility (one that filed within the last three years) and (ii) the logarithm of the distance between patient i and the nearest nonbankrupt facility (one that never files during our sample period). We cluster standard errors at the patient-ZIP-code level. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively. See Table 7 for details.