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HEALTHCARE PROVIDER BANKRUPTCIES

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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.

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1 Introduction

Over the last few decades, healthcare firms have increasingly relied on risky debt. Total debt in the U.S. healthcare sector has doubled in just the five years between 2019 and 2024. As their debts grow, many healthcare firms struggle to keep up with their debt obligations. As a result, Moody's rates 80% of debt issued by healthcare firms as speculative grade (Landi, 2022) and healthcare bankruptcies have hit a record high (Mathurin, 2024).[1]

High leverage and frequent bankruptcies are not inherently a problem for financial stakeholders. Many firms use Chapter 11 bankruptcy, which is designed to maximize value through efficient renegotiation of debt obligations without liquidation.[2] However, even absent liquidations and closures, bankruptcies may still impose negative externalities on non-financial stakeholders. This possibility is particularly important in healthcare: regulators and the public worry that provider bankruptcies could harm patients through downsizing, cost-cutting, and worsening care (Goldstein, 2019).[3] In spite of these concerns, we know of no empirical evidence on the impacts of healthcare provider bankruptcies.

In this paper, we provide a first look at the impact of healthcare provider bankruptcies. We focus on the $200 billion U.S. nursing home industry for its size, heavy reliance on public financing through Medicare and Medicaid, and the vulnerability of its patients. Furthermore, regulators collect uniquely detailed data on the industry, including payroll-based records for every worker in the industry and health assessments for virtually every patient.

To estimate the causal impact of a provider's bankruptcy filing on its staffing, we employ a matched difference-in-differences (DiD) event study design on high-frequency payroll and census data covering nearly every nursing home worker in the United States. We first document that staffing levels, occupancy, and the composition of staff certifications do not substantially change after a bankruptcy filing. However, while total staffing levels remain largely unchanged, the detailed nature of our data allows us to observe an increase in staff turnover after facilities file for bankruptcy. In the year after a bankruptcy filing, weekly

[1]In addition to the usual tax benefits (Graham, 2000), high levels of debt may be uniquely attractive for healthcare providers for other reasons. Multiple government agencies—including HHS, HUD, and USDA—subsidize debt financing for providers. Debt also creates a perception of financial precarity that helps healthcare providers negotiate higher reimbursement rates (Liu, 2022; Gandhi and Olenski, 2024).

[2]In our sample, 94% of healthcare firms continue to operate during and after a Chapter 11 filing.

[3]Aiming to avoid bankruptcies, state and federal governments invest substantially in the financial health of healthcare providers. Examples include: (i) targeting healthy provider margins when setting reimbursement rates (e.g., MedPAC, 2025), (ii) subsidizing financing (e.g., GAO, 1995; GAO, 2024), making $135B in Provider Relief Fund payments during the pandemic, and (iv) supporting providers in high-profile bankruptcies (e.g., Harrison, 2024).

worker separations increase by 10% of the mean relative to control facilities. While new workers replace exiting workers almost one for one, the high turnover results in a meaningful shift toward care being provided by recent hires with little tenure at the facility. We also find evidence that turnover is explained by bankrupt facilities struggling to retain experienced workers rather than making cost-cutting layoffs: facilities pay higher wages and employ more costly and inefficient contract workers after filing, and turnover is higher among firms in more competitive labor markets.

Bankruptcy-induced turnover might degrade care by disrupting the relationship between patients and staff. Nursing home care is extremely labor intensive and involves frequent intimate interactions requiring familiarity with patients' individual clinical needs. We explore this possibility in two ways. First, we use a matched DiD to estimate how bankruptcy affects a facility's performance on unannounced health inspections. We find that bankruptcies result in a variety of violations related to both staffing and quality of care. Second, we estimate the impact of bankruptcies on patient health outcomes using an instrumental variables approach that addresses patient selection into or away from bankrupt facilities. We leverage the well-documented fact that nursing home patients are highly distance-elastic (Hackmann, 2019; Gandhi, 2023) and instrument for whether a patient receives care at a bankrupt facility with their probability of choosing a bankrupt facility based on a distance-based discrete-choice demand model (Kessler and McClellan, 2000; Einav, Finkelstein, and Mahoney, 2024). Importantly, the instrument derives its variation in each patient's choice of facility based exclusively on the proximity of that patient's home ZIP code to nearby facilities. It does not condition on a patient's actual choice of facility and therefore avoids potential selection bias. Additionally, the instrument varies over time for residents of the same home ZIP code based on which nearby facilities have recently filed for bankruptcy. This variation over time allows us to include ZIP code fixed effects in our regression, mitigating concerns about bias due to unobserved geospatial variation in health.

Using this instrumental variables approach, we find that bankruptcies result in substantially worse care. Most notably, receiving care from a recently bankrupt facility increases a patient's probability of hospitalization by 1.44 percentage points (4.1% of the mean). Such hospitalizations represent major harms to patient health, as they imply the patient's health deteriorated sufficiently to qualify for admission to the hospital. We also find that bankruptcies harm patients in other meaningful ways. Bankruptcies increase the use of physical restraints and bedsores by 77% and 14% of the mean, respectively. Regulators use both of these as indicators of low-quality care and potential abuse.

Finally, we validate that staff turnover is the mechanism through which bankruptcies harm patients. We demonstrate this using a survey experiment completed by 247 current and former nursing home staff. Participants read hypothetical scenarios in which a nurse cares for patients. In the control group, the nurse has one year of tenure at a facility. In the randomly assigned treatment group, the same scenarios feature a nurse with one *week* of tenure. Participants then draw on their real-world experience to predict patient outcomes. Comparing responses across groups, we find that replacing a high-tenure nurse with a low-tenure nurse causally increases the rate of negative patient outcomes by 10 percentage points (44% of the control-group mean). In a separate experiment with the same participant pool, we find that bankruptcies cause voluntary turnover, supporting our empirical evidence. Participants evaluating a bankrupt facility estimate voluntary turnover to be 47% higher than participants evaluating an otherwise identical non-bankrupt facility.

Our findings have several implications for regulators and policymakers. First, regulators should closely monitor all healthcare provider bankruptcies, not only liquidations and closures. We show that even bankrupt providers that continue to operate may experience adverse effects. In our setting, these adverse effects stem from bankruptcy-induced staff turnover and have dramatic implications for patients, including abuse and hospitalizations.

Second, regulators could consider reducing the frequency of healthcare provider bankruptcies. One way to accomplish this is to reduce providers' use of debt financing. Regulators could make debt financing less attractive by cutting existing debt subsidies and excluding interest payments from consideration in determining reimbursement rates. A more extreme policy might impose limits on debt financing for healthcare firms. This limit would be analogous to the ubiquitous capital requirements that regulators impose on critical industries such as banking, insurance, and utilities. Finally, regulators could subsidize financially distressed healthcare firms, giving them additional time to improve operations and avoid bankruptcy.

Third, to the extent that bankruptcies cannot be avoided, regulators could create new procedures for provider bankruptcies that mitigate bankruptcy-induced turnover. In the extreme, regulators could temporarily take control of failed providers, as they do for failed banks. In doing so, regulators could guarantee employment for current employees until a financially healthy buyer acquires the operations. A more minor adjustment could be requiring the payment of pre-bankruptcy employee wages upon filing.[4] Moreover, guaranteeing employees' wages obviates the requirement that they be notified of the bankruptcy as creditors.

[4] This requirement builds on an existing rule that post-bankruptcy wages must be paid as they come due.

Related Literature. Our paper provides the first empirical examination of healthcare provider bankruptcies. We most directly contribute to the rapidly growing healthcare finance literature on the implications of providers' financial decisions for patients (Adelino, Lewellen, and Sundaram, 2015; Eliason et al., 2020; Gandhi, Song, and Upadrashta, 2020; La Forgia, 2022; Forgia et al., 2022; Liu, 2022; Adelino, Lewellen, and McCartney, 2022; Gandhi, Song, and Upadrashta, 2022; Duggan et al., 2023; Lin et al., 2023; Richards and Whaley, 2024; La Forgia and Bodner, 2024; Andreyeva et al., 2024; Gupta et al., 2024; Bruch, Roy, and Grogan, 2024; Richards, Shi, and Whaley, 2024; Aghamolla et al., 2024).

Within the healthcare literature, our study relates to several strands of research. First, we relate to a large body of work on the nursing home industry (Gertler, 1989; Gertler and Waldman, 1992; Grabowski, Gruber, and Angelelli, 2008; Lin, 2014; Hackmann, 2019; Friedrich and Hackmann, 2021; Cheng, 2023; Gandhi, 2023; Gandhi et al., 2024b; Hackmann, Pohl, and Ziebarth, 2024; Cheng, 2024; Olenski and Sacher, 2024; Einav, Finkelstein, and Mahoney, 2024). Second, we relate to several studies on staff turnover (Gray, Phillips, and Normand, 1996; Shields and Ward, 2001; Propper and Van Reenen, 2010; Bartel et al., 2014; Antwi and Bowblis, 2018a; Gandhi, Yu, and Grabowski, 2021; Gandhi and Ruffini, 2022; Gandhi et al., 2024b,a; Moscelli et al., 2025) and disruptions in care more broadly (Agha, Frandsen, and Rebitzer, 2019; Agha et al., 2022; Sabety, Jena, and Barnett, 2021; Sinsky et al., 2022; Sabety, 2023; Olenski, 2023; Sabety et al., 2024; Schwab, 2025).

Finally, we contribute to a finance literature on how corporate bankruptcies impact non-financial stakeholders such as workers (Berk, Stanton, and Zechner, 2010; Falato and Liang, 2016; Brown and Matsa, 2016; Baghai et al., 2021; Ellias, 2022; Gortmaker, Jeffers, and Lee, 2022; Araujo et al., 2023; Graham et al., 2023) and customers (Hortaçsu et al., 2011; Matsa, 2011; Hortaçsu et al., 2013; Phillips and Sertsios, 2013; Antill and Hunter, 2023).

2 Empirical Setting

2.1 Nursing Home Industry

Nursing homes, known formally as skilled nursing facilities (SNFs), are certified by Centers for Medicare and Medicaid Services (CMS) to provide skilled nursing services, rehabilitative therapy, and other healthcare services requiring residence in an institutional setting. The industry consists of more than 15,000 facilities employing approximately 1.4 million staff serving more than 1.3 million residents daily. Residents are highly vulnerable, older, and suffer from physical ailments and cognitive impairments. Quality is shockingly low: one in three nursing home patients on Medicare experiences harm or death as a result of low-quality care (OIG, 2014).

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. Nursing home quality is a long-standing concern (U.S. Senate, 1960, 2024), so regulators carefully monitor the quality of nursing home care along a number of dimensions detailed below.

The industry's reliance on government financing and the vulnerability of nursing home patients has led to substantial regulatory scrutiny. As a result, regulators collect uniquely detailed data on the industry, including payroll-based records for every worker in the industry and health assessments for virtually every patient. Through several Freedom of Information Act (FOIA) requests, we collect all of these records and link them to the universe of corporate bankruptcy records. Thus, by focusing on nursing homes we can form a comprehensive industry-wide picture of how bankruptcies impact facilities, workers, and patients.

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; Friedrich and Hackmann, 2021; CMS, 2019), 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 (CMS, 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 to implement processes specific to each facility and provide care tailored to each patient. Correspondingly, it is 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. Therefore, having a consistent care team likely yields better health outcomes, a finding shown to be true across many healthcare contexts (Wasson et al., 1984; Nyweide et al., 2013; Antwi and Bowblis, 2018b; Sabety, Jena, and Barnett, 2021).

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 (CMS, 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. Facilities are also evaluated based on patients' health outcomes using two sources of data. The first are mandated resident assessments performed at least quarterly for all patients and on approximately days 5, 14, 30, 60, and 90 during Medicare stays. These detail patients' health status—e.g., cognitive function, bedsores, performance of activities of daily living—and care—e.g., whether they have been physically restrained, catheterized, or given antipsychotics. The second are Medicare claims that provide information such as whether a resident required hospitalization after being admitted to a nursing home. CMS utilizes indicators of poor quality care from both assessments (e.g., physical restraints) and claims (e.g., hospitalization) when constructing quality ratings for nursing homes.

2.2 Bankruptcy

Firms that cannot pay their debts use Chapter 11 bankruptcy to restructure debt, renegotiate contracts, or sell assets. Most commonly, firms file Chapter 11 aiming for a "reorganization" under which creditors exchange some of their existing debt claims for equity claims on the firm's future profits.[5] 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 stakeholders 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 negative publicity of a bankruptcy filing can create operational problems, as we discuss next.

Information revealed by a bankruptcy filing. A bankruptcy filing makes the firm's financial distress salient to creditors, the general public, and employees. The bankrupt firm

[5] Firms can also use Chapter 11 to repay lenders by selling assets (11 U.S. Code §363), which typically occurs through an acquisition or a liquidation. 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. 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).

must notify its creditors when it files. The filing is a public record that can be viewed by anyone. Therefore, media outlets regularly report on bankruptcy filings, including filings by small private firms. Further, if employees have unpaid wage claims or pension claims, the firm must notify them when it files. Therefore, employees will likely learn when their employer files for bankruptcy.

Prior to a bankruptcy filing, employees might be unaware of their employer's financial condition. A private firm has virtually no obligation to disclose any financial information to employees. Even employees of public nonbankrupt firms might not scrutinize public disclosures sufficiently carefully to learn if their employer is struggling financially. For this reason, a bankruptcy filing could dramatically increase the share of employees who are aware that their employer is struggling financially. Indeed, Antill and Hunter (2023) show that a large share of consumers know which firms are in bankruptcy, but virtually no consumers know which nonbankrupt firms are struggling financially. In this sense, a bankruptcy is a public disclosure that the firm cannot meet its debt obligations. Once employees learn about a bankruptcy, they might be concerned for several reasons, which we discuss next.

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. Specifically, employees are likely concerned that a bankruptcy could lead to liquidation, which would eliminate their jobs. Therefore, employees might seek other work and quit preemptively before they are fired in a liquidation.

Additionally, employees might worry about the firm's ability to pay their wages. 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 how developments in a bankruptcy can exacerbate employee concerns, implying that employee turnover might take some time to materialize after a bankruptcy filing.

Healthcare provider bankruptcies. There are a few features of healthcare and nursing home bankruptcies that are worth highlighting. The first is that healthcare providers' excessive debt might stem from a number of industry-specific incentives beyond the usual tax advantages of debt (Graham, 2000). A number of government programs subsidize debt financing for healthcare providers. For example, The Department of Housing and Urban Development (HUD) guarantees mortgages for approximately 15% of nursing homes, totaling more than $20 billion (Goldstein, 2019). HUD also reports guaranteeing over 400 mortgages for hospitals. Similar subsidies are offered by other departments, such as Health and Human Services' Health Center Facility Loan Guarantee Program and the United States Department of Agriculture's Rural Development program. Additionally, research suggests that providers are able to utilize the apparent financial precarity created by high levels of debt to negotiate higher reimbursement rates (Liu, 2022; Gandhi and Olenski, 2024).

Second, Chapter 11 rarely leads to liquidation or closure for healthcare firms. In our sample, only 6% of bankrupt facilities close. Similarly, Section 5 shows 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. 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.

Third, 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 staff care for patients whose memory or cognition may be highly limited and whose frailty means that adverse outcomes may be quite severe.

Fourth, 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 impact 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 policymakers do about these losses? To answer these questions, we introduce an informal model of the decisions leading to a bankruptcy filing.

Our informal model begins with the decision of how much debt to issue (low versus high leverage). Choosing low leverage makes a bankruptcy filing unlikely. However, choosing low leverage causes the firm to forgo the benefits of high leverage. High 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, 2022). 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" and struggle to pay interest on its debt and to repay or refinance 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 or continue operating. When a firm files for bankruptcy, it will reorganize, be acquired, or liquidate. In a successful reorganization or acquisition, the firm can reduce its debt obligations, relieving financial distress (Section 2.2). In a liquidation, the firm shuts down, an outcome typically avoided by healthcare firms (Section 2.2). However, employees might mistakenly believe that the risk of liquidation is high, scaring them into quitting prematurely. Employee separations are exacerbated by the fact that a bankruptcy filing is a public record that often attracts media attention, potentially alerting employees to the firm's distress. In contrast, a firm's financial struggles prior to bankruptcy might be harder for employees to observe. Consistent with a bankruptcy increasing the salience of distress, Antill and Hunter (2023) show that a bankruptcy filing dramatically increases awareness of a firm's distress. As a result, a bankruptcy filing can be costly if it makes distress more salient to a firm's employees, triggering employee departures.

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, a similar approach to filing for bankruptcy without the negative publicity and salience for employees. However, this approach is rarely successful: most debt restructurings are quickly followed by bankruptcy filings (Donaldson et al., 2020). Second, the firm 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.

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 changes experienced by bankrupt firms in the weeks around bankruptcy to changes experienced by matched control firms that never file for 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 policymaker prevent costly bankruptcies? A policymaker who wants to avoid bankruptcy filings could limit the leverage of healthcare firms. Alternatively, the policymaker 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 policymaker 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.[6]

4 Administrative Data

We use a variety of datasets in our analysis. Sections 4.1 details our data on nursing homes, including payroll-based data detailing the shifts of all nursing home workers. Section 4.2 details our claims and assessment data on nursing home patients. Finally, Section 4.3 details our data on U.S. healthcare bankruptcies.

4.1 Nursing Home Data

We detail three datasets below that we use to examine nursing home operations. The first are payroll-based records detailing staff shifts at the facility. The second are annual data on facility characteristics. The last are records from unannounced health inspections measuring

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

facilities' compliance with federal standards for operation and care.

Payroll Based Journal (PBJ). Starting in the fourth quarter of 2016, Centers for Medicare and Medicaid Services (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 PBJ.

We obtained the PBJ from CMS via two federal FOIA lawsuits (Gandhi v. Centers for Medicare and Medicaid Services, 2019 and 2020). We use the records to observe the hours worked by each nursing staff member on each day during our sample. Each record details the facility, the worker's facility-specific worker ID, their role—e.g., registered nurse (RN), licensed practical nurse (LPN), or certified nursing assistant (CNA)—whether the worker is an employee or a contractor, and the precise amount of time worked that day. Note that since worker IDs are facility-specific, we cannot track workers employed at multiple facilities in our sample across their employment relationships. In total, our dataset contains 1.1 billion staffing shifts for 7.5 million different employment relationships.

We analyze all RN, LPN, and CNA records from the fourth quarter of 2016 through the first quarter of 2020. We do not extend our sample into the COVID-19 pandemic for two reasons. 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.

Provider Data. We use two sources of annual data on nursing homes' characteristics for 2010 through 2019. The first is CMS' published Provider Information files, which we use to distinguish whether facilities are for-profit and the number of CMS-certified beds at the facility. The second is Brown's LTCFocus database, which we use for annual measures of facilities' occupancy rate and the fraction of care-days reimbursed by Medicare.

Health inspections. We utilize detailed data from CMS on unannounced health inspections at each facility for the period of 2010 through the first quarter of 2020. Professional health inspectors employed by the state conduct unannounced inspections at each facility approximately annually to assess compliance with federal requirements. 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.

4.2 Patient Data

We use three linked administrative datasets from CMS that detail care and health outcomes for nursing home patients from 2010 through 2019.

Medicare Master Beneficiary Summary File (MBSF). The MBSF contains enrollment information for all Medicare beneficiaries. For deceased beneficiaries, it includes their date of death. 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 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. Healthcare providers must file a claim to receive reimbursement from Medicare. The claim includes detailed information regarding the care that the patient received, including procedures, diagnosis codes, dates, and the amount charged by the provider. We use the Medicare Inpatient (IP), Medicare Outpatient (OP), and the Medicare Provider Analysis and Review (MedPAR) claims files. The Medicare IP and OP files provide raw claims data, and the MedPAR file provides an aggregation of inpatient nursing home and hospital claims to the episode level. We exclude patients enrolled in Medicare Advantage from our health outcomes analysis because we do not observe all of their claims.

These data detail patients' Medicare-covered care before, during, and after their nursing home stay. Since Medicare coverage of nursing home care typically requires a preceding 3-night hospital stay, we identify patients' most relevant diagnosis using claims from the hospital stay immediately preceding the nursing home admission. Additionally, we observe when nursing home patients are hospitalized. High rates of hospitalization are considered an indicator of poor quality nursing home care.

Long Term Care Minimum Data Set (MDS). The Omnibus Budget Reconciliation Act of 1987 requires nursing homes to regularly submit detailed health assessments for each resident to CMS. The administrative database containing the assessments is known as the MDS. Nursing homes submit MDS assessments for each resident quarterly, annually, at admission, at discharge, or if there is a major change in status. CMS requires assessments to be submitted for all residents, including those who are uninsured or have private insurance. 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.

MDS assessments contain hundreds of measures detailing the resident's health status and current care. These include physical ailments—such as bedsores and infections—and cognitive function. MDS assessments also detail the resident's care, such as whether the resident was physically restrained, catheterized, or given antipsychotics.

4.3 Bankruptcy Data

The Public Access to Court Electronic Records (PACER) service provides electronic public access to federal court records. Since bankruptcy courts are federal courts, PACER contains detailed information on every bankruptcy case. We download PACER records to construct a comprehensive dataset covering every corporate Chapter 11 bankruptcy involving a healthcare firm.[7] For each of these "healthcare bankruptcies," we observe the bankruptcy filing date and identifying information such as the name, address, and employer-identification number (EIN) for the bankrupt company.

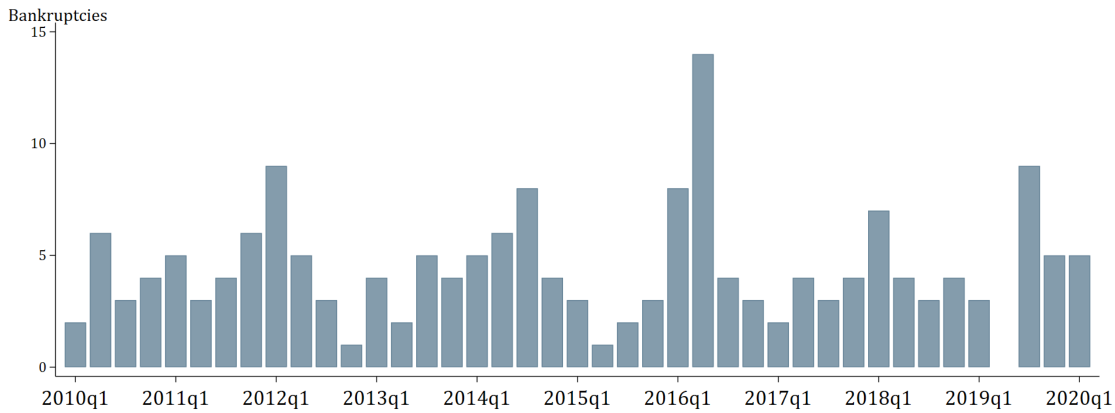
Through a Freedom of Information Act request, we obtain a novel dataset containing the EIN for every healthcare provider in the National Plan and Provider Enumeration System (NPPES) database. We also obtain EINs for parent companies, allowing us to observe each subsidiary of a bankrupt parent company. We then merge the bankruptcy and CMS data by EIN, name, and address to identify which healthcare facilities file for Chapter 11 bankruptcy. 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). See Appendix B for details.

Our final dataset contains all bankruptcies filed from 2010Q1-2020Q1. Figure 1 illustrates

[7]We ensure comprehensive coverage using the Federal Judicial Center's (FJC) publicly available dataset, which is constructed from PACER data and covers all bankruptcies filed since 2008. This dataset includes a binary variable identifying healthcare bankruptcies, which is derived from a mandatory question on the bankruptcy petition. Using this variable, we identify the full set of healthcare bankruptcies filed from 2010Q1-2020Q1. We locate each bankruptcy on the PACER website using the filing court and docket number, then we download the necessary variables that do not appear in the FJC (e.g., the EIN).

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 quarters.

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 and 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. A facility is "treated" if it files for Chapter 11 during our sample period. We match each treated facility to up to five "control facilities" that do not file for bankruptcy during our sample period. Specifically, let Y_f denote the year in which a treated facility f files for bankruptcy. We use facility-year level data from Brown's LTCFocus to construct a dataset containing all facilities (treated and control) in the year $Y_f - 1$ prior to the bankruptcy. Using this dataset, we calculate ten decile bins for each of the following three variables: (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 reimbursed by Medicare.[8] We construct a

[8]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.

"cohort" $c(f)$ by matching the treated facility f to up to five control facilities, which must share the same decile bin as the treated facility for each variable in year $Y_f - 1$. We select the five controls at random if more than five control facilities meet the criterion. We repeat this process for each treated facility, choosing controls without replacement so that each control facility appears in at most one cohort. This matching procedure, which is sometimes called "coarsened exact matching," ensures that treated facilities are compared to controls that are similar in size, bed utilization, and patient characteristics.

Table 1: Balance Table

	Treated Facilities	Control Facilities	|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. This table compares matched bankrupt facilities (treated) to facilities that never file for bankruptcy (controls). Columns (1) and (2) present means for each variable in treated and control facilities as of 52 weeks before 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 52 weeks before bankruptcy.[9] Facilities are statistically indistinguishable across matching variables. 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 slightly greater in the control group. However, the difference is 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 $\alpha_{w,c(f)}$.[10] In doing so, 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 ($w > T_{c(f)} + 52$).[11] We use (ii), the year

[9]Note that even though a substantial majority of residents receive some Medicare-covered nursing home care, only a small fraction of resident-days are covered by Medicare. This is due to the fact that Medicare only covers a resident's initial rehab and therapy care. This coverage typically lasts only a few weeks and is limited to 100 days. Our health outcomes analysis focuses on Medicare enrollees for a period of up to 90 days after admission. This sample includes the majority of nursing home admissions and contains the vast majority of Medicare-covered nursing home care.

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

[11]We include cohorts in which the bankruptcy filing occurs in the first 52 weeks or last 52 weeks of our

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 reference period. The key parameters of interest are β^S and β^L, which capture the short-term and long-term effects of bankruptcy.[12]

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

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

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 led 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 C1 presents the associated high-frequency event studies

sample. This results in an unbalanced panel but allows us to maximize our sample size.

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

(equation 2), focusing on the year immediately prior to and the year immediately after the 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
Short-Term Effect	-6.090	-14.458	-0.423	0.198	-0.090	-0.108
	(5.044)	(11.298)	(0.390)	(0.236)	(0.151)	(0.222)
Long-Term Effect	-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. Each observation is a facility-week. Standard errors are in parentheses and are clustered by nursing home chain. See Figure C1 for event studies. 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 a facility each day and then 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 C1) 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 to meaningful reductions in the volume of patients served in either the short 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 staffing measures to be "per 100 beds" because 100 certified beds is a typical size for a nursing home.[13] In the second and third columns of Table 2, we present results from estimating equation (1) using these two staffing measures as outcome variables.[14] 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 C1) 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). Moreover, since these slight staffing reductions are met with slight occupancy reductions, any effects on staffing per resident are even more muted. In sum, our estimates indicate that bankruptcies do not result in immediate or dramatic reductions in total staffing levels.

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 multiple 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 nurse hours 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. Our estimates suggest no statistically significant effects on short- 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 C1).

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

Staff tenure is a key input into a nursing home's quality of care (Section 2.1). Workers with a longer tenure have greater familiarity with the facility and its residents. In this section, we find that bankruptcies increase turnover and reduce staff tenure at bankrupt facilities.

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

[14] Throughout, we winsorize staffing variables at the 1st and 99th percentiles.

Measuring turnover and tenure. Since the Payroll Based Journal (PBJ) includes virtually all daily shifts for nursing home workers, we can precisely measure the hire date, separation date, and tenure for each individual staff member. We identify each worker's hire and separation dates at a given facility using the dates of their first and last shifts, respectively.[15] For each staff member in each week, we measure their tenure by counting the number of days prior to that week that they worked a shift at the facility. Figure C2 presents the distribution of nursing staff tenure in 2019. We observe considerable variation in tenure with a large mass of recent hires, consistent with previous work documenting high turnover in the industry (Gandhi, Yu, and Grabowski, 2021). In our analysis, we distinguish low-tenure staff (i.e. new staff) as those who have worked fewer than 60 shifts—i.e., have fewer than 60 shifts with recorded hours in the PBJ—at the facility. This cutoff corresponds to approximately the 25th percentile of employee tenure, which is 62 shifts.[16]

An important limitation of the PBJ data is that workers are not tracked across facilities. Therefore, workers with low tenure at a given facility may have considerable experience in the industry. Still, such workers will lack facility-specific human capital, including familiarity with the facility's residents and their clinical needs. Moreover, data from one state with facility-specific tenure in the PBJ linked to workers' self-reported industry experience indicate that the two measures are highly correlated (Figure C3).

Staff turnover. To test whether a bankruptcy filing increases staff turnover, we estimate equation (1) using weekly measures of worker separations and hires as the outcome variables. In examining separations, the dependent variable is the number of workers who separated from the facility that week. As with our other staffing measures, separations are normalized by facility size so that the outcome is measured as separations per 100 beds. The first column of Table 3 displays the results, which show that the weekly number of worker separations per 100 beds spikes by 0.146 (10.3% of the dependent variable sample mean) in the year after a bankruptcy filing. In the long term (i.e., more than one year after the filing), the weekly number of worker separations remains 0.123 higher at bankrupt facilities (8.7% of the sample mean).

To determine whether and how facilities replace these departing workers, we measure the number of new workers starting at a facility in a given week per 100 beds. The second column of Table 3 displays the results. We find an economically and statistically significant

[15] We exclude hires occurring in the first two weeks and separations occurring in the last two weeks of reporting for each facility, as these may represent sample censoring rather than hires and separations.

[16] In order to ensure we are able to measure tenure and turnover accurately, we restrict our sample to facility-weeks for which the previous 13 weeks (≈ 90 days) were fully reported in the PBJ.

Table 3: The Effect of Bankruptcy on the Turnover and Tenure of Nursing Staff

	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.146***	0.118**	-1.420***	0.937***
	(0.034)	(0.046)	(0.463)	(0.309)
Long-Term Effect	0.123***	0.146***	-3.160***	1.741***
	(0.038)	(0.055)	(0.474)	(0.599)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.42	0.37	0.87	0.63
Mean	1.42	1.35	49.03	14.36
Observations	459,804	459,804	459,804	459,804

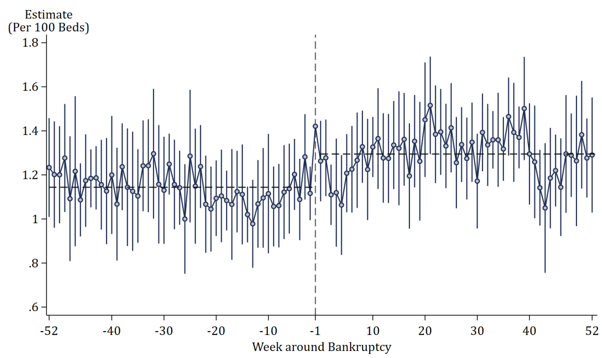
Note. This table examines nursing staff turnover and tenure. The dependent variable "Separations" represents the number of departing workers in a facility-week per 100 beds. The dependent variable "Hires" represents the number of new workers in a facility-week per 100 beds. The dependent variable "High Tenure" is the number of workers who have worked at least 60 shifts at the facility per 100 beds. The dependent variable "Low Tenure" is the number of workers who have worked fewer than 60 shifts at the facility per 100 beds. Each observation is a facility-week. Standard errors are in parentheses and are clustered by nursing home chain. See Figure 2 for event studies. See Appendix C.6 for point estimates for each nursing staff role. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

increase in new worker hires after a bankruptcy filing. The weekly number of new hires per 100 beds increases by 0.118 (8.7% of the sample mean) in the year after a bankruptcy filing and by 0.146 (10.8% of the sample mean) in the long term. Importantly, these increases are of roughly the same magnitude as the increases in separations, which is consistent with our earlier finding that overall staffing levels remain relatively constant after a bankruptcy.

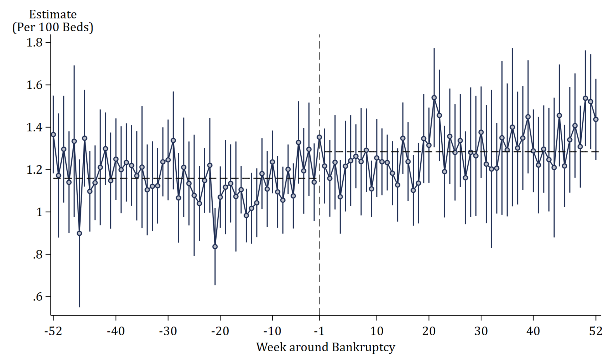
Figure 2 panels (a) and (b) present the weekly dynamic treatment effects (equation 2) for separations and hires, respectively. We do not observe noticeable pre-trends in either during the year leading up to bankruptcy. While noisy, the weekly estimates are consistent with our finding that both separations and hires are elevated in the year after bankruptcy.

Staff tenure. When highly tenured staff separate and are replaced by new hires, it changes the distribution of worker tenure at a facility. In this way, turnover induced by bankruptcies may result in patients receiving more care from new hires and less from tenured staff. We study this by estimating equation (1) using an outcome variable that is the total number high-tenure workers at a given facility in a given week. As with our other staffing measures, we normalize this measure by facility size to be per 100 beds. The third column of Table 3 presents our estimates, which imply that the number of high-tenure workers declines by about 1.4 workers per 100 beds in the year after a bankruptcy and remains depressed by

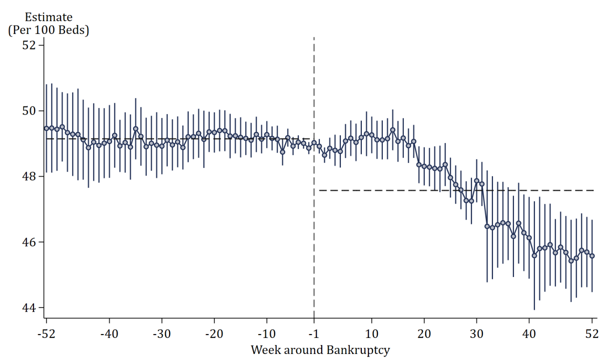
Figure 2: Dynamic Effects of Bankruptcy on Nursing Staff Turnover and Tenure



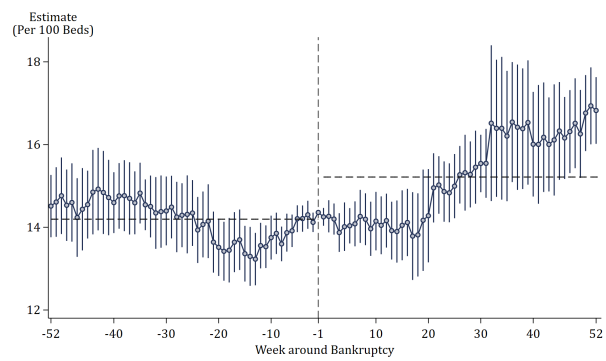
(a) Separations



(b) Hires



(c) High-Tenure Workers



(d) Low-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 separating from the facility per 100 beds. In panel (b), the dependent variable is the number of workers joining the facility per 100 beds. In panel (c), the dependent variable is the number of workers who have worked at least 60 shifts at the facility (High-Tenure Workers) per 100 beds. In panel (d), the dependent variable is the number of workers who have worked fewer than 60 shifts at the facility (Low-Tenure 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 3 for point estimates. See Appendix C.6 for tenure changes for each nursing staff role.

about 3.2 workers per 100 beds in the long term. Column 4 repeats the exercise for low-tenure staff with fewer than 60 shifts worked at the facility. As expected, we find that the number of low-tenure staff increases by about 0.9 and 1.74 workers per 100 beds in the short and long term, respectively. These respectively represent 6.5% and 12.1% increases relative to the sample means.

We also estimate weekly dynamic treatment effects on the composition of staff tenure. Figure 2 panels (c) and (d) respectively present weekly treatment effects on the number of high- and low-tenure workers per 100 beds. In both cases, we do not observe pre-trends prior to the bankruptcy. In the weeks after a bankruptcy filing, the number of high-tenure workers falls while the number of low-tenure workers spikes. Interestingly, it takes more than a quarter for the effects to be statistically discernible. This may represent the time required for staff to find alternative employment opportunities.

Robustness. We perform a variety of tests in the Appendix that demonstrate the robustness of our findings on turnover and tenure. In Appendix C.4, we show that the estimated shift in tenure composition is robust to alternative measures, including the hours and share of hours worked by low- and high-tenure staff (Table C1). Likewise, we show in Appendix C.5 that the result is robust to alternative thresholds defining low- and high-tenure workers (Table C2). Finally, in Appendix C.6 we examine effects on turnover and tenure separately for RNs, LPNs, and CNAs. We find slight differences in the precise nature and magnitude of effects but that all three experience substantial turnover and shifts in tenure.

Evidence of Voluntary Turnover. The post-bankruptcy increase in staff turnover that we observe could be driven by workers through voluntary separations (i.e., quitting) or by the firm through involuntary separations (i.e., layoffs). Section 7 uses a survey experiment to show that affirmative evidence that turnover in response to bankruptcy is likely voluntary. In particular, we find that workers randomly assigned to a hypothetical of employment at a bankrupt firm express serious concerns about what bankruptcy entails for the quality and stability of their jobs. More importantly, these workers assigned to the bankrupt firm are dramatically more likely to say that they would seek alternative employment.

In this section, we summarize three empirical patterns—detailed more fully in Appendix C.7—that are consistent with our survey results but inconsistent with the alternative of bankruptcy-induced turnover being involuntary. First, note that facilities should only lay off tenured staff and replace them with new hires if it confers a financial benefit. We find this to be far from the case. Table C4 examines facilities' wage payments reported on Medicare cost reports and finds that the average hourly nursing wage rises by 2% after a bankruptcy filing.

It would be puzzling for facilities to intentionally lay off their most experienced workers while simultaneously paying more per hour of staffing. Table C5 suggests that one source of this increase in costs is that bankrupt facilities shift towards employing more contract labor in lieu of employees. Contract nursing staff are both more expensive and generally considered less effective than employed nursing staff (Bowblis et al., 2024). Indeed, the use of contract staff to address turnover has been shown to result in poor quality care (Castle and Engberg, 2007). This shift towards more expensive and less effective workers is most consistent with a facility struggling to maintain staffing levels. Finally, Table C6 shows that turnover increases most in competitive labor markets where workers have more employment options. This, too, is most consistent with bankrupt facilities struggling to retain staff rather than intentional layoffs.

6 Quality of Care and Patient Health

In the previous section, we showed that workers leave when a nursing home files for bankruptcy, shifting the composition of labor toward low-tenure workers. Changes to staffing could meaningfully affect patient care because nursing home care is intimate and labor-intensive. 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. We then use administrative data on Medicare claims and resident health assessments to study the impact of bankruptcy on patients' health outcomes.

6.1 Health Inspections

CMS requires states to inspect all nursing homes once every twelve months on average. These "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 whether facilities' practices and policies are in compliance with federal standards. 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, potentially generating "complaint deficiencies." On average, facilities receive approximately two complaint deficiencies between each standard inspection.

In addition to examining facilities' total number of standard and complaint citations, we also specifically examine two CMS-defined categories of violations (CMS 2021) where the effects of bankruptcy-induced turnover might plausibly manifest. The first are "nursing services" violations, such as insufficient staffing or failing to provide CNAs with performance reviews. Many of these have been shown to harm patient care (Lin, 2014; Trinkoff et al., 2017; Friedrich and Hackmann, 2021). The second are "quality of care" violations, such as inappropriate tube feeding or unnecessary use of bedrails as a restraint. These violations often contravene clinical standards and may be implemented as a means to save money and staff time (Mitchell et al., 2004, 2016).

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 the 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., $\tau \geq 2$).[17] 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-by-inspection-time fixed effects $\alpha_{\tau,c(f)}$ and cohort-specific facility fixed effects $\rho_{f,c(f)}$ to estimate a stacked DiD. The coefficients β^S and β^L 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 4. In the first column, our dependent variable is the total number of deficiency citations received in a standard inspection. We find that performance on these inspections worsens immediately after a bankruptcy filing: relative to matched control facilities, bankrupt facilities are cited for 0.69

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

Table 4: Performance on Health Inspections After Bankruptcy

	Standard Citations	Complaint Citations	Nursing Services Citations	Quality of Care Citations
Short-Term Effect	0.689*	0.365	0.078**	0.278*
	(0.371)	(0.333)	(0.035)	(0.166)
Long-Term Effect	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.

more deficiencies during their first standard inspection after the bankruptcy. The treatment effect is equal to 11% of the dependent-variable sample mean. For reference, the 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 estimate the effect on the total number of complaint deficiencies. The second column of Table 4 displays the results. While our point estimates suggest an increase in complaint deficiencies, the effect is very imprecisely estimated.

Next, we estimate the effect of bankruptcy on citations related to nursing services. The third column of Table 4 presents the results. We find that a bankruptcy filing increases nursing services citations by 0.078 in the short term (44% of the dependent-variable sample mean). We examine each type of nursing services citation separately in Appendix E.3 and find that violations are concentrated in three areas: (i) staffing that the inspector deems inadequate, (ii) failure to provide in-service training and evaluation to CNAs, and (iii) failure to post daily staffing and resident census numbers. These represent substantial human resource failures that are consistent with a facility struggling to maintain sufficient and sufficiently trained staffing.

Finally, we study the impact of bankruptcy filings on quality of care, using a dependent variable equal to the total number of violations that CMS categorizes as related to quality of care. The fourth column of Table 4 shows that a bankruptcy filing causes a short-term increase of 0.28 (16% of the mean) quality of care citations. In Appendix E.4, we consider each quality of care citation separately. There are many citations that CMS categorizes as relating to quality of care. While almost all point estimates indicate an increase in citations after bankruptcy, most are imprecisely estimated. Two stand out as experiencing increases that are statistically significant: citations for unnecessary tube feeding and improper use of bedrails. Both contravene clinical guidelines and are often implemented as a means to save staff time and compensate for inexperience or incompetence. In Section 6.2, we show complementary results suggesting that staff use bedrails inappropriately to physically restrain residents against their will.

Across all four of the dependent variables considered in Table 4, we find no statistically significant evidence that bankruptcy has a long-term effect on inspections. The lack of significance might suggest that the harms of bankruptcy to patient health and safety along these dimensions are highly transitory. This is particularly plausible given that inspectors require facilities to take corrective actions in response to citations and often re-visit facilities to verify that the facility followed through with implementing the corrective action.

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).

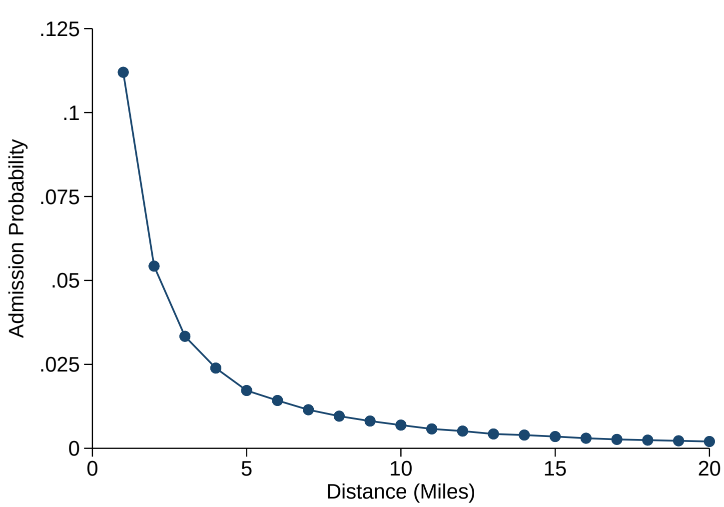
6.2 Patient Health Outcomes

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.

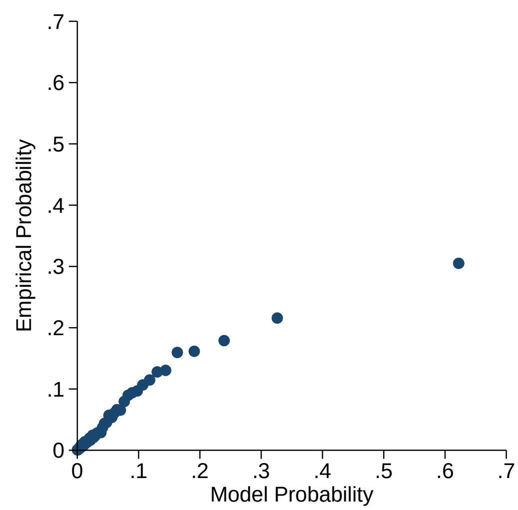
6.2.1 Instrumental-Variables Approach

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, 2023) or because facilities adjust their admission or discharge policies after a bankruptcy filing (Gandhi, 2023; Hackmann, Pohl, and Ziebarth, 2024).

Figure 3: 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.

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 sensitive to distance when choosing between nursing homes (Rahman et al., 2014; Hackmann, 2019; Gandhi, 2023; Einav, Finkelstein, and Mahoney, 2024). Figure 3 panel (a) affirms this, showing that a patient is far more likely to choose a facility 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 3 panel (a) shows that the 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.[18] 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.

Our primary specification uses a distance-based discrete-choice model to calculate our instrument.[19] 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, $d(z(i), f)$

[18] 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).

[19] Our instrument builds on Kessler and McClellan (2000); Geweke, Gowrisankaran, and Town (2003); Garthwaite, Ody, and Starc (2022); Cheng (2023); Olenski and Sacher (2024); 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.

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 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 $t(i)$.[20] 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 3 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 3 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).

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

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 fixed effect for the patient's primary diagnosis from their pre-admission hospital stay.[21] 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 3, 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.

We provide evidence supporting the exclusion-restriction assumption, although it is fundamentally untestable. Figure G1 shows the instrument has little correlation with observable patient characteristics likely to influence or predict health outcomes. Our fixed effects and controls also play a key role in the plausibility of the exclusion-restriction assumption. Facility fixed effects ensure that systematic differences in quality of care across nursing homes

[21] 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."

do not influence our estimate of β (equation 8). 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 sicker patients in a way not fully captured by the 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 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 5, 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 5 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 5 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 5 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.

We are unable to identify the precise cause of the additional bankruptcy-induced hospitalizations. In the fourth column of Table 5 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 5 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).[22]

[22]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

Table 5: 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 (bedsores), 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 estimate equation (8) using outcomes Y_i that are measured on these 30-day assessments. Our estimates, which we display in Table 5 panel (b), indicate meaningful degradations in care after bankruptcy. First, recently-bankrupt nursing homes appear substantially more likely to physically restrain patients.[23] The first column of panel (b) shows that a bankruptcy increases the probability that a patient will be physically restrained by 1.5 percentage points, 77% of the sample mean. It is important to emphasize that the 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 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). 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 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 staff assistance required for toileting. The CMS quality rating system penalizes the use of catheters to disincentivize facilities from using medically unnecessary catheterization to

but would not include quarterly and annual assessments taken after transitioning from Medicare coverage to Medicaid or private pay.

[23] 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).

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, there may be 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 find that nursing home bankruptcies cause staff turnover (Section 5). Bankruptcies also cause a decline in patient care processes and health outcomes (Section 6). In this section, we use an online survey experiment to show that staff turnover is the mechanism by which bankruptcies harm patients. Specifically, our survey of current and former nursing home staff shows that bankruptcies cause voluntary staff departures and staff turnover causes poor patient health outcomes.

We ran our pre-registered survey experiment (AEARCTR-0010335) from November 2022 to December 2022 on the Cint (formerly Lucid) platform. We obtained 247 high-quality responses from RNs, LPNs, and CNAs with experience working in nursing homes.[24] The survey included two sections. Both sections feature randomized variation. First, we estimate how bankruptcies affect workers' willingness to seek alternative employment. Second, we show that replacing existing staff with new low tenure staff causes poor patient health outcomes. We provide additional details and results in Appendix A. Appendix A.1 details the design of the survey experiment, Appendix A.2 details our statistical approach and results, and Appendix A.3 provides additional evidence on mechanisms.

Section 1: Bankruptcy and voluntary separations. In the first section of the survey, each nurse participant reads a description of a hypothetical nursing home job. We construct the job description provided to each participant to match the role, wage, and location of the participant's most recent nursing home employment. This construction helps participants imagine how they would behave if they were to hold this hypothetical job.

The key randomized variation is in the financial health of the hypothetical nursing home. We randomly assign each participant to one of three groups with equal probability. In the control group, the hypothetical facility 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 ask the 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 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

[24] We use a standard attention check to confirm that each participant is carefully reading the survey questions.

effects associated with the Distressed treatment, though these are smaller in magnitude.

These results demonstrate that real nursing home staff will likely search for another job when faced with the prospect of working at a recently bankrupt facility. This holds true whether asked about their own behavior or their beliefs about others' behavior. This finding strongly suggests that the bankruptcy-induced turnover in Section 5.3 stems from voluntary separations and complements our empirical results in Appendix C.7. In Appendix A.3, we present both numerical and free-text responses showing that participants faced with the prospect of working at bankrupt facilities expressed concerns that bankruptcy could mean an impending closure. Similarly, participants are concerned that bankruptcy is a negative signal about management, job quality, and wage stability at the facility.

Section 2: Quality and efficiency of care from low-tenure staff. In the second section of the survey, participants assess hypothetical scenarios involving hypothetical nurses caring for patients. Each patient scenario involves care tasks typical to the participant's most recent nursing staff role. We consulted with a RN to identify and write realistic descriptions of typical care tasks for RNs, LPNs, and CNAs.

The key randomized variation in the hypothetical is in the tenure of the staff member.[25] We randomly assign each survey participant to one of two groups. In the control group, the hypothetical nurse performing each task has one year of tenure at the facility. In the treatment group, the hypothetical nurse has one week of tenure at the facility. All other details in the hypothetical scenarios are identical across groups.[26]

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

We compare participant responses across randomly assigned groups. Relative to the control-group participants, participants in the treatment group report: (i) a 9.7 percentage point greater probability of harmful mistakes (44% of the control-group mean), and (ii) a completion time that is 6 minutes longer (14% of the control-group mean). Both effects

[25] In order to avoid responses that associate new staff with bankruptcies, we present this section before the hypothetical testing for voluntary turnover in response to bankruptcies.

[26] Both groups compare the hypothetical nurse to a nurse with two years of tenure. This design choice mitigates experimenter demand: if participants simply state poor results for the nurse with lower tenure, then we should detect no effect between the one-year-versus-two-year comparison (control) and the one-week-versus-two-year comparison (treatment). See Appendix A for details.

are statistically significant ($p < 0.01$).[27]

These results demonstrate that nursing home workers believe that low-tenure workers are less efficient and more likely to provide poor care that harms patients. This finding indicates that the bankruptcy-induced turnover in Section 5.3 likely drives the poor post-bankruptcy care and adverse health outcomes we find in Section 6.

In summary, our survey experiment confirms that nursing home staff are likely to voluntarily separate in response to a bankruptcy filing. Further, the survey experiment shows that replacement staff with less tenure are both less efficient and provide worse care. While these results are based on survey participants evaluating hypothetical scenarios, they are still informative for at least two reasons. First, all participants are current and former nursing home workers, so their responses are based on real-world experience in the industry. Second, our across-participant design mitigates experimenter-demand concerns because participants are unaware of the treatment.[28]

8 Conclusion

This paper leverages administrative and survey data from the healthcare sector to study the implication of healthcare provider bankruptcies in the U.S. nursing home industry. Using a DiD design, we show that a Chapter 11 bankruptcy filing increases worker turnover and the fraction of care provided by low-tenure staff at the bankrupt nursing homes. We further find that this increase in turnover coincides with poor performance on unannounced health inspections. We then employ an instrumental variables approach to identify the effects of bankruptcy on patient health outcomes. We find that patients receiving care at recently bankrupt facilities are more likely to be hospitalized, to be physically restrained, and to have bedsores. Finally, using an online survey experiment of current and former nursing home staff, we confirm the linkage between bankruptcy filings, voluntary turnover, and low quality care that harms patients.

[27] We cluster standard errors by participant to adjust for participants evaluating multiple scenarios.

[28] In other words, treatment-group participants do not know they are treated or how their descriptions differ from those viewed by control-group participants.

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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.[29] Participants provide answers for the same nurses and see the same randomized length of tenure for the less experienced

[29] 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.

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.[30] 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:

[30]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.[31]

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

[31] 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.

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

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 Belief		0.431***		0.569***
		(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.

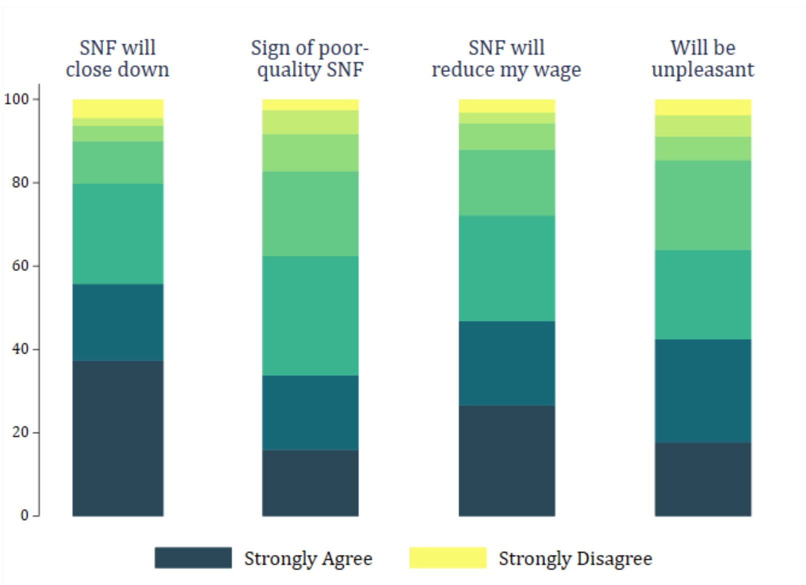


Figure A1: Concerns Influencing Willingness to Work at Facility

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.[32]

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

[32] 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 shifts. 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.

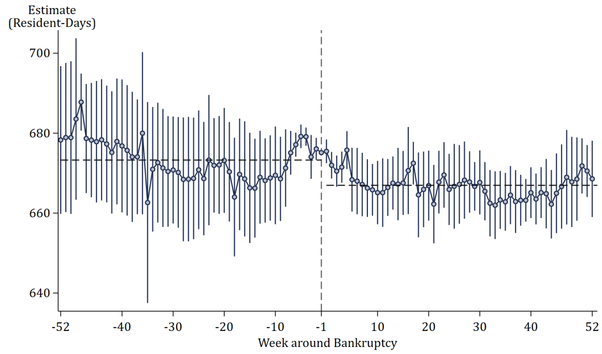
C Staffing Analysis Appendix

This appendix contains additional results related to the analysis of Section 5.

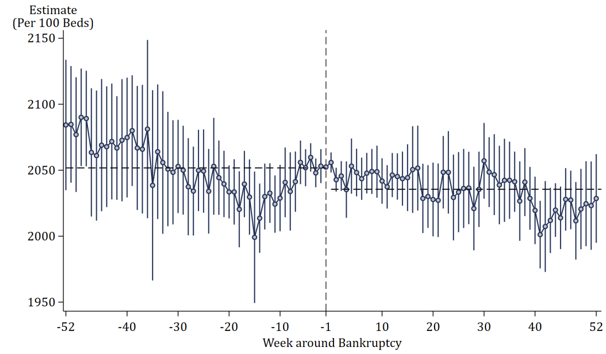
C.1 Event Studies of Occupancy, Staffing Levels, and Skill Mix

Figure C1 shows high-frequency event studies (equation 2) for dependent variables related to total staffing, patient occupancy, and skill mix. While these figures show that a bankruptcy filing impacts total staffing and occupancy, the effect sizes are quantitatively quite small. There appears to be no statistically significant effect on skill mix.

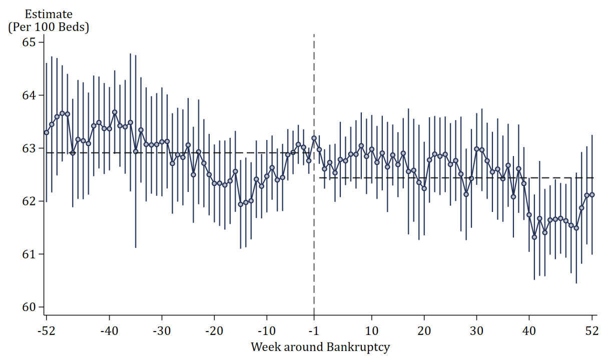
Figure C1: Event Studies of Occupancy, Staffing Levels, and Skill Mix



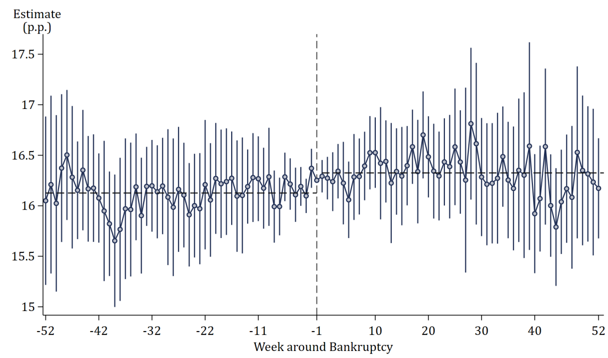
(a) Resident-Days



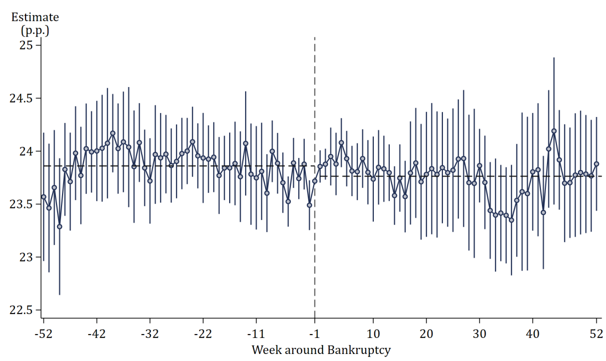
(b) Hours per 100 Beds



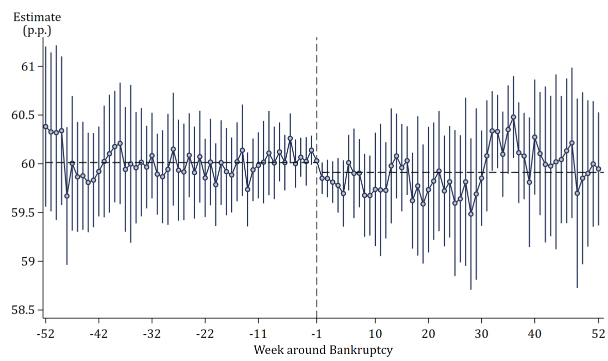
(c) Employees per 100 Beds



(d) RN Share



(e) LPN Share



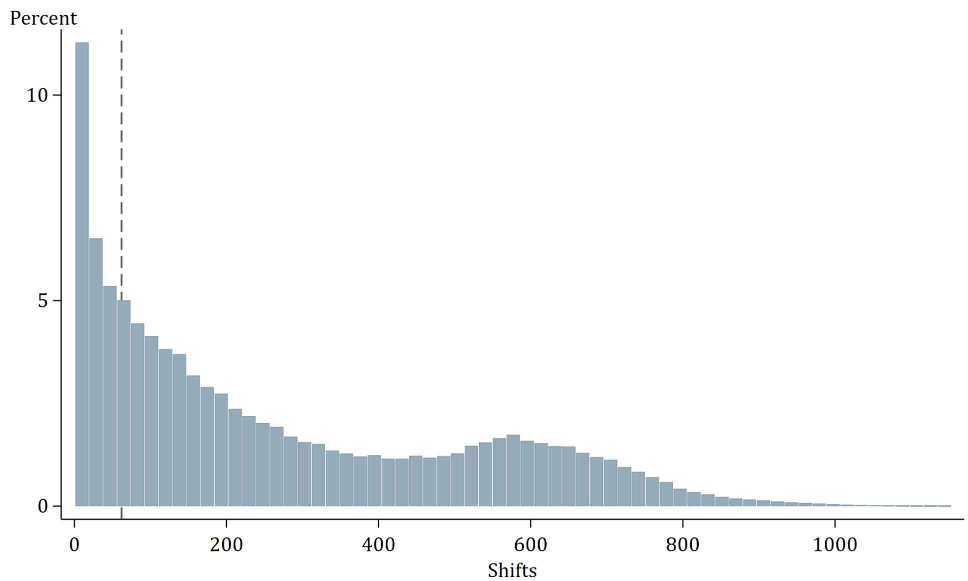
(f) CNA Share

Note. We estimate the dynamic difference-in-differences specification (2) to calculate bankruptcy treatment effects in each week around the filing date. In 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. Standard errors are clustered by nursing home chain and 95% confidence intervals are displayed. See Table 2 for point estimates.

C.2 Distribution of Nursing Home Staff Tenure

Figure C2 plots the distribution of worker tenure and depicts the 25th percentile of 62 shifts.

Figure C2: Distribution of Employee Tenure

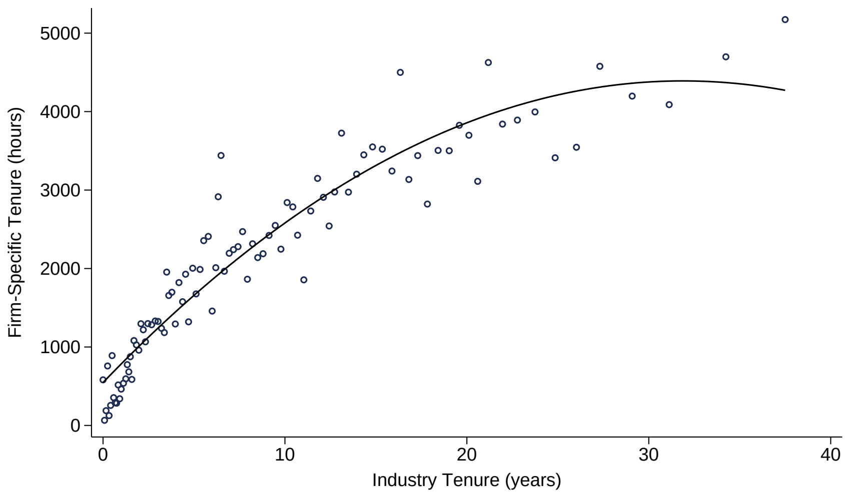


Note. This figure plots the distribution of staff tenure: the number of shifts that a particular staff member has worked at a particular facility. The sample is restricted to shifts in 2019 in order to minimize the number of staff whose tenure is censored by the start of the sample. We plot the percentage of workers (on the y axis) with a particular number of shifts of tenure (on the x axis). The vertical dashed line denotes the 25th percentile, which is 62 shifts.

C.3 Correlation between Firm-Specific and Industry Tenure

In general, the PBJ does not track nurse's experience across facilities. However, in an unpublished manuscript, Ashvin Gandhi, Andrew Olenski, Karen Shen, and Krista Ruffini use administrative data from Illinois linking PBJ records to employees' reported experience in the industry. They find that nurse tenure at a given facility is highly correlated with nurse experience in the industry. Figure C3 is reproduced from this unpublished manuscript.

Figure C3: Firm-Specific and Industry Tenure for CNAs in Illinois



Note. This figure is reproduced from an unpublished manuscript by Ashvin Gandhi, Andrew Olenski, Karen Shen, and Krista Ruffini. It demonstrates the relationship between firm-specific tenure in the 2022 PBJ and self-certified lifetime experience of Illinois CNAs. The CNA experience data were collected for an Medicaid reimbursement reform in Illinois intended to incentivize facilities to employ experienced CNAs.

C.4 Alternative Measures of Tenure Composition

Table 3 shows that a bankruptcy filing shifts facilities toward employing more low-tenure workers and fewer high-tenure workers. Table C1 shows that this is also true when measuring the composition of worker tenure by the number and share of hours worked by low- and high-tenure workers.

Table C1: Robustness to Alternative Measures of Tenure Composition

	Hours		Hour Share	
	High Tenure	Low Tenure	High Tenure	Low Tenure
Short-Term Effect	-44.913***	29.300***	-2.054***	2.054***
	(14.248)	(9.134)	(0.482)	(0.482)
Long-Term Effect	-96.082***	48.270***	-3.262***	3.262***
	(13.010)	(14.841)	(0.710)	(0.710)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.86	0.58	0.53	0.53
Mean	1,692.67	363.12	81.66	18.34
Observations	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. 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.

C.5 Alternative Thresholds Distinguishing Low and High Tenure

The main text presents results in which low-tenure staff are defined as those that have worked fewer than 60 shifts at the facility, as this is approximately the 25th percentile of employee tenure of 62 shifts. Table C2 shows our findings are robust alternative thresholds of 30 shifts and 90 shifts.

Table C2: Robustness to Alternative Thresholds for Low and High Tenure

	≥ 30 Shift Tenure			< 30 Shift Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
Short-Term Effect	-31.974***	-1.276***	-1.070***	15.524***	1.276***	0.584***
	(12.237)	(0.261)	(0.388)	(5.496)	(0.261)	(0.222)
Long-Term Effect	-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 × 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

	≥ 90 Shift Tenure			< 90 Shift Tenure		
	Hours	Hour share	Employees	Hours	Hour share	Employees
Short-Term Effect	-77.207***	-3.513***	-2.305***	58.952***	3.513***	1.724***
	(19.179)	(0.834)	(0.618)	(13.385)	(0.834)	(0.432)
Long-Term Effect	-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 × 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 Results by Nursing Staff Role

Finally, we examine whether the increases in turnover are concentrated among RNs, LPNs, or CNAs. To do this, we construct role-specific hire and separation rates for RNs, LPNs, and CNAs. Our estimates suggest that turnover increases for all three, with slight differences in nature and magnitude.

Table C3 also indicates substantial rates of both separations and new hires for LPNs and CNAs. Notably, while the estimates also indicate an increase in RN separations that are a substantial percentage of the sample mean, these do not appear to be compensated by a corresponding increase in new RN hires. Given that we do not observe a shift away from RN hours in Table 2, this necessarily implies that the increase in RN separations are compensated predominantly by increasing the number of hours that retained RNs work. Figures C4, C5, and C6 plot weekly treatment-effect estimates from equation (2). While the individual weekly estimate are noisy, they show patterns consistent with the short-run effects in our pooled difference-in-differences.

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

Panel (A). RNs

	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.024***	0.009	-0.126	0.039
	(0.007)	(0.008)	(0.079)	(0.094)
Long-Term Effect	0.014*	-0.002	-0.634***	-0.044
	(0.008)	(0.012)	(0.172)	(0.161)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.28	0.27	0.89	0.57
Mean	0.21	0.19	7.92	2.33
Observations	459,804	459,804	459,804	459,804

Panel (B). LPNs

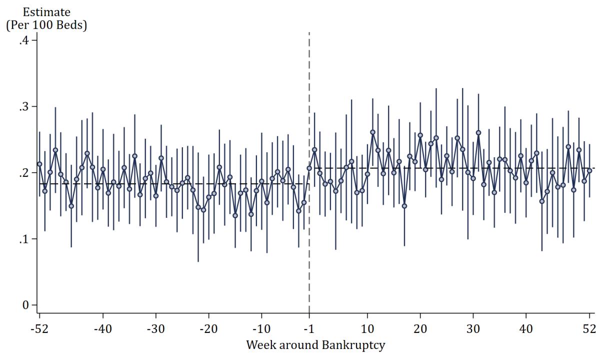
	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.046***	0.035***	-0.425***	0.241***
	(0.008)	(0.008)	(0.126)	(0.086)
Long-Term Effect	0.038***	0.043***	-0.703***	0.520***
	(0.009)	(0.009)	(0.168)	(0.109)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.32	0.30	0.84	0.55
Mean	0.28	0.26	11.27	2.96
Observations	459,804	459,804	459,804	459,804

Panel (C). CNAs

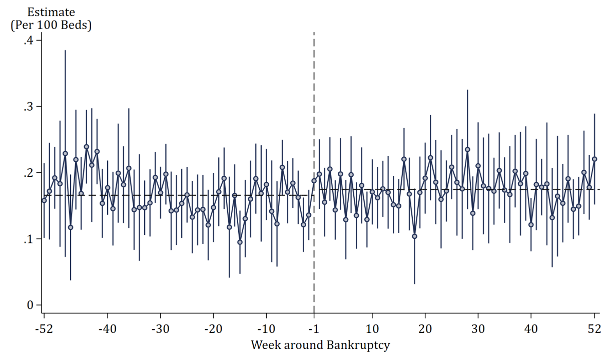
	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.079***	0.077**	-0.854***	0.643***
	(0.025)	(0.032)	(0.310)	(0.189)
Long-Term Effect	0.072**	0.103***	-1.816***	1.246***
	(0.029)	(0.037)	(0.431)	(0.409)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.38	0.34	0.86	0.60
Mean	0.92	0.89	29.71	9.01
Observations	459,804	459,804	459,804	459,804

Note. In each panel of this table, we limit our PBJ sample to include only nurses in one specific role and then we replicate Table 3. In panel (a), we limit the sample to only include RNs. In panels (b) and (c), the sample includes only LPNs and CNAs, respectively. See Table 3 for details.

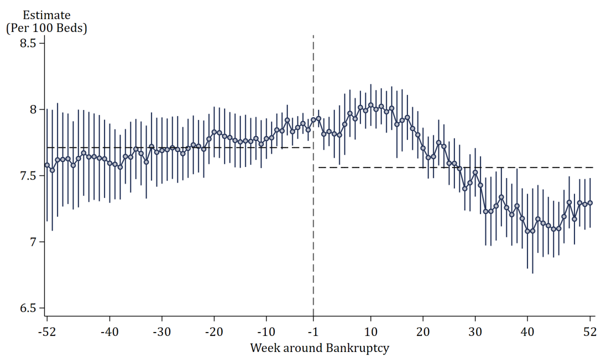
Figure C4: Dynamic Effects of Bankruptcy on Registered Nurse (RN) Staffing Turnover



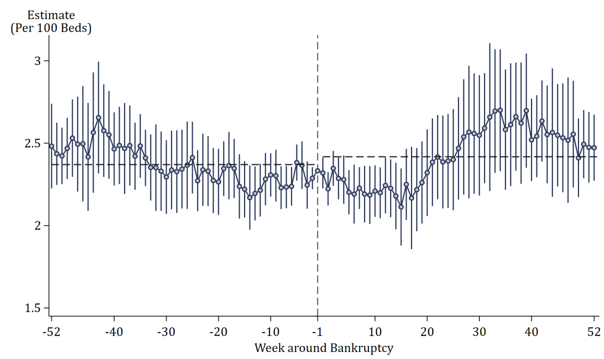
(a) RN Separations



(b) RN Hires



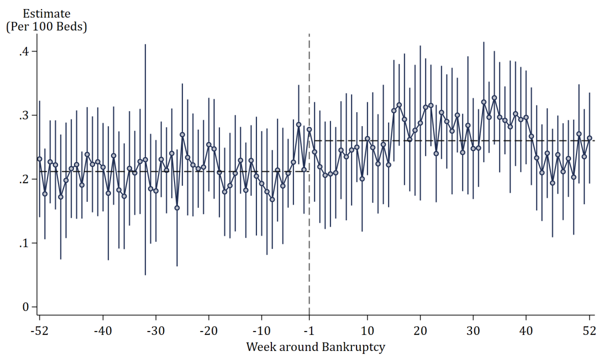
(c) High-Tenure RNs



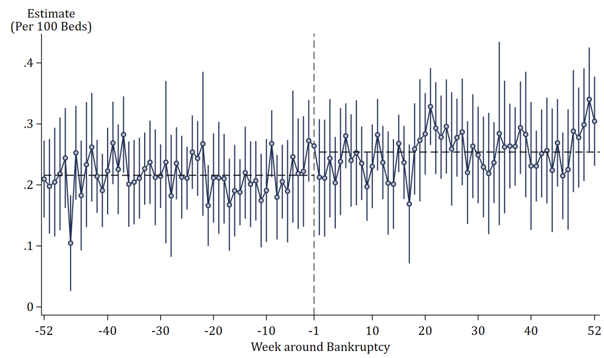
(d) Low-Tenure RNs

Note. We limit our PBJ sample to include only RNs and then we replicate Figure 2. This figure presents the results. See Figure 2 for details.

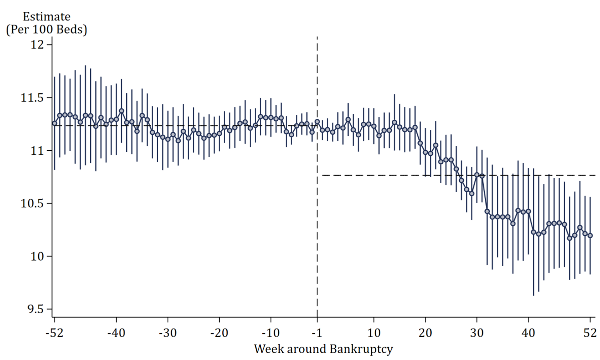
Figure C5: Dynamic Effects of Bankruptcy on Licensed Practical Nurse (LPN) Staffing Turnover



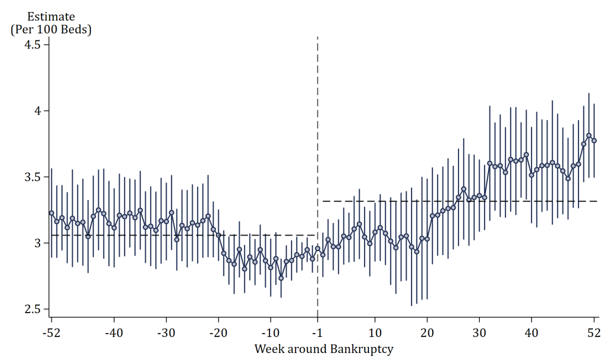
(a) LPN Separations



(b) LPN Hires



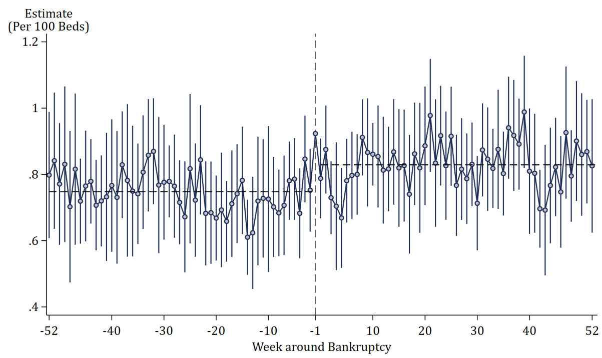
(c) High-Tenure LPNs



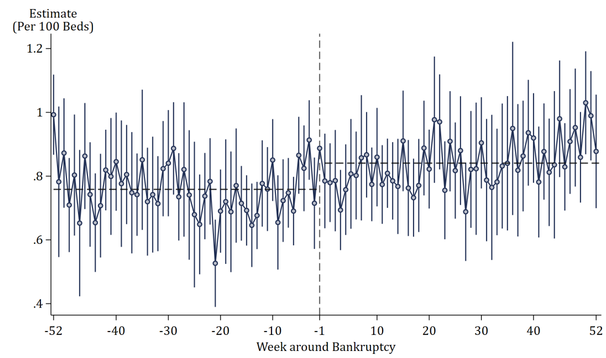
(d) Low-Tenure LPNs

Note. We limit our PBJ sample to include only LPNs and then we replicate Figure 2. This figure presents the results. See Figure 2 for details.

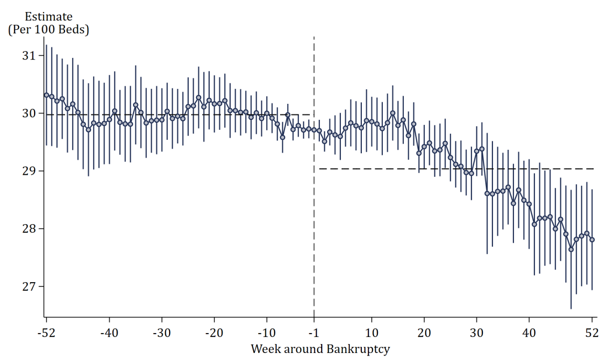
Figure C6: Dynamic Effects of Bankruptcy on Certified Nursing Assistant (CNA) Staffing Turnover



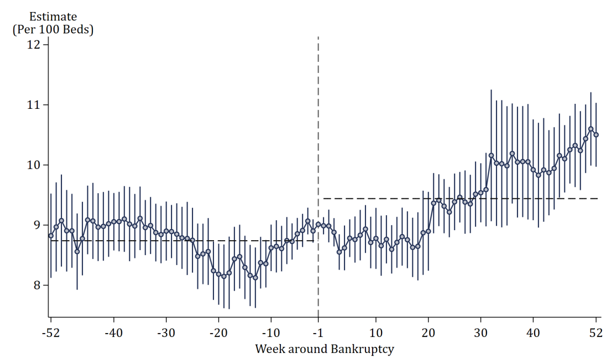
(a) CNA Separations



(b) CNA Hires



(c) High-Tenure CNAs



(d) Low-Tenure CNAs

Note. We limit our PBJ sample to include only CNAs and then we replicate Figure 2. This figure presents the results. See Figure 2 for details.

C.7 Evidence of Voluntary Turnover

In this section, we present three pieces of evidence consistent with bankruptcy-induced turnover being voluntary. The first is that staff wages increase after the bankruptcy, which suggests difficulty recruiting and retaining staff. The second is that facilities shift towards contract workers. The fact that these workers are both more expensive and less effective likewise suggests difficulty in recruiting and retaining employees. Finally, we show that effects are largest in labor markets where workers are likely to have more alternative employers.

Table C4: 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.

Wages. We use data from Medicare cost reports—known formally as the Healthcare Cost Report Information System (HCRIS)—to investigate changes in worker wages after bankruptcy. The cost reports contain annual filings with the average wage over each fiscal year. We drop the fiscal year that covers the date of the bankruptcy filing, but the results are robust to including these as either treatment or control observations. Table C4 estimates the matched stacked difference-in-differences model with the natural log of average hourly wages as the dependent variable. We find that average wages rise by 2.4% after a bankruptcy filing. This increase is similar across nursing staff types.

Contract labor. Next, we find 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

C5. 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 C5 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.

Labor market concentration. 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 index bankruptcy filing for its cohort. That is, we use a time-invariant measure of market concentration for each facility in the regressions.

Figure C8 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.

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. Table C6 presents the estimates from the following dynamic specification, a "triple-difference" analogue of equation (1) in the main text:

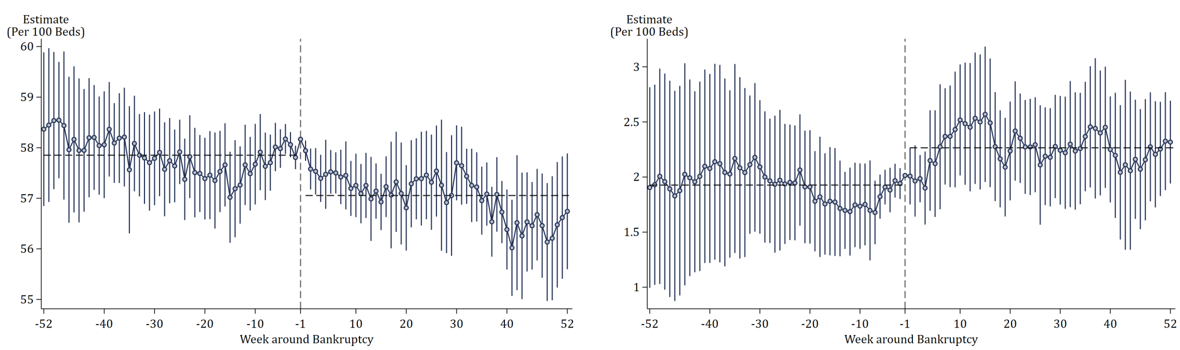
$$\begin{aligned} y_{f,w} = {} & \delta \cdot B_f \mathbf{1}\{w < T_{c(f)} - 52\} + \delta_H \cdot B_f \mathbf{1}\{w < T_{c(f)} - 52\} \cdot \widetilde{HHI}_f \\ & + \beta^S \cdot B_f \mathbf{1}\{T_{c(f)} \leq w \leq T_{c(f)} + 52\} + \beta^S_H \cdot B_f \mathbf{1}\{T_{c(f)} \leq w \leq T_{c(f)} + 52\} \cdot \widetilde{HHI}_f \\ & + \beta^L \cdot B_f \mathbf{1}\{w > T_{c(f)} + 52\} + \beta^L_H \cdot B_f \mathbf{1}\{w > T_{c(f)} + 52\} \cdot \widetilde{HHI}_f \\ & + \alpha_{w,c(f)} + \rho_{f,c(f)} + \epsilon_{f,w} \end{aligned} \tag{13}$$

Table C5: Staffing Responses to Bankruptcy by Employment Contract

	Wage Workers			Contract Workers		
	Hours	Hour Share	Employees	Hours	Hour Share	Employees
Short-Term Effect	-24.210**	-0.824***	-0.758**	8.288**	0.781***	0.340*
	(11.597)	(0.260)	(0.340)	(3.895)	(0.196)	(0.178)
Long-Term Effect	-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 C7 for event studies.

Figure C7: Staffing Responses to Bankruptcy by Employment Contract

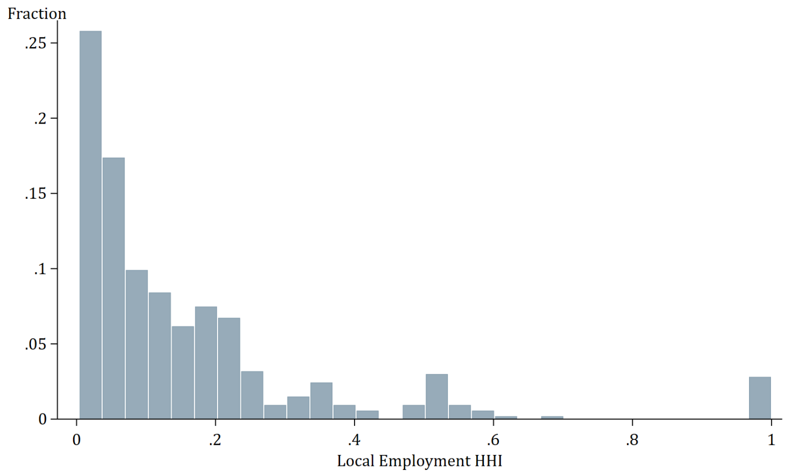


(a) Wage Workers

(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 C5 for point estimates.

Figure C8: 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.

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. The fact that the effects are strongest in markets where workers have more alternatives is most consistent with turnover being voluntary.

Table C6: The Effect of Bankruptcy on the Turnover and Tenure of Nursing Staff

	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.222***	0.225***	-2.348***	1.567***
	(0.040)	(0.047)	(0.467)	(0.357)
Short-Term Effect $\times \widetilde{HHI}$	-0.096	-0.135***	1.180***	-0.802**
	(0.060)	(0.046)	(0.382)	(0.355)
Long-Term Effect	0.178***	0.174***	-3.683***	1.657***
	(0.034)	(0.048)	(0.529)	(0.485)
Long-Term Effect $\times \widetilde{HHI}$	-0.067	-0.038	0.651	0.062
	(0.046)	(0.050)	(0.426)	(0.524)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week $\times$ Cohort	Yes	Yes	Yes	Yes
R^2	0.42	0.37	0.87	0.63
Mean	1.42	1.35	49.03	14.36
Observations	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 "Separations" represents the number of departing workers in a facility-week per 100 beds. The dependent variable "Hires" represents the number of new workers in a facility-week per 100 beds. The dependent variables in the third and fourth columns are the number of high-tenure or low-tenure employees per 100 beds, respectively. Each observation is a facility week. Standard errors are in parentheses and are clustered by nursing home chain. See Figure 2 for event studies. See Appendix C.6 for point estimates for each nursing staff role. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

D Facility Closures and Changes in Ownership

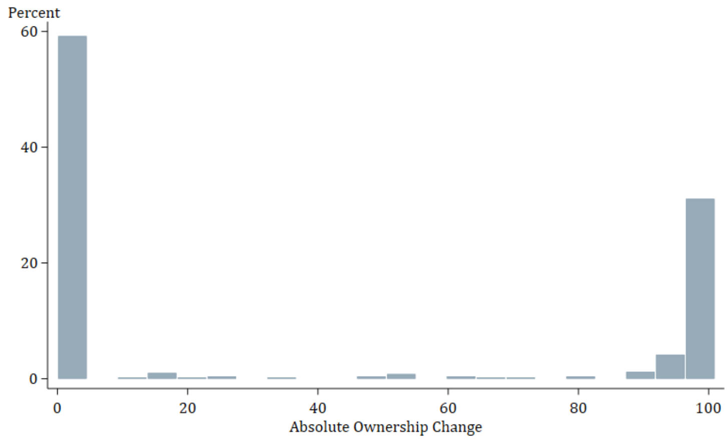
This paper studies the effects of bankruptcy on employees and patients. In doing so we focus on Chapter 11 reorganizations, during which debtors continue to operate while bankruptcy proceedings take place. However, it is possible for firms to shut down as a result of the restructuring even after filing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

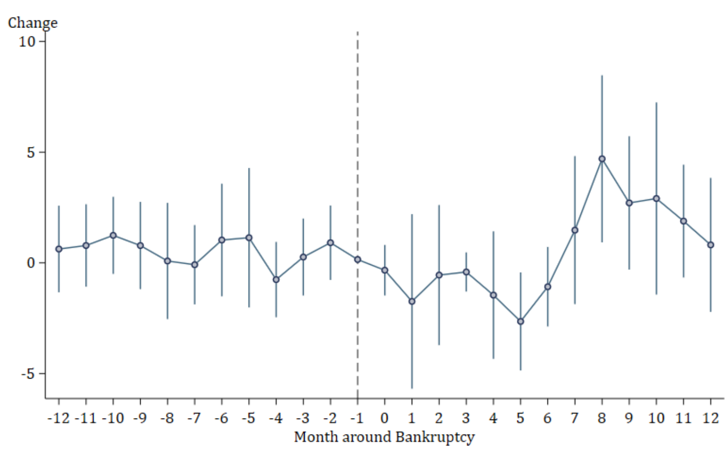
We formally investigate ownership changes around bankruptcy through a difference-in-differences analysis of monthly percent ownership changes at the facility level. The dynamic event study of Figure D2 shows a delayed increase in ownership changes, with a noticeable five percentage point average effect 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

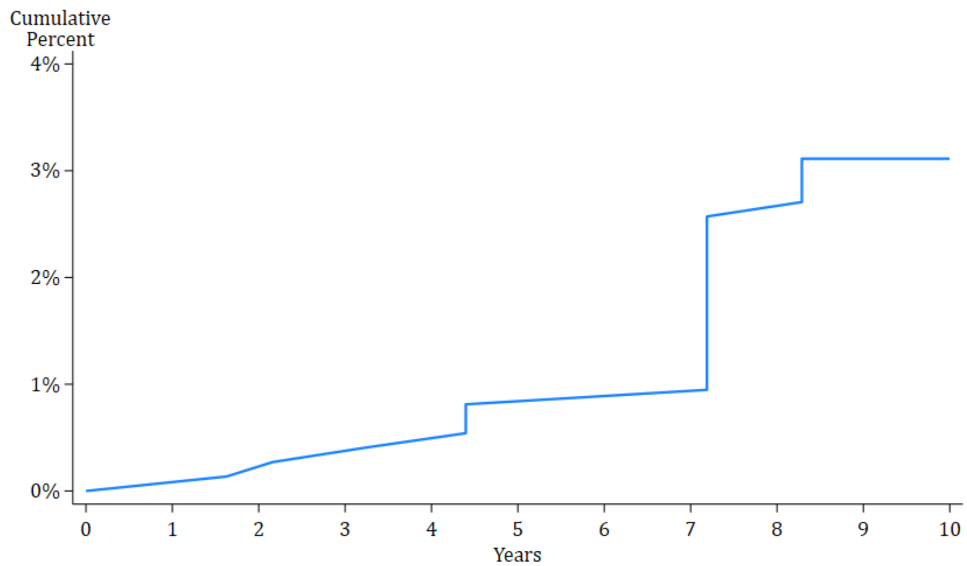


Note. This figure shows how ownership changes around a bankruptcy filing.

D.1 Private Equity Ownership of Bankrupt Facilities

Figure D3 shows that fewer than 4% of the bankrupt facilities in our sample experienced a private equity LBO in the ten years preceding the bankruptcy. Because of this, our bankruptcy treatment effects are unlikely to pick up the treatment effect of private equity ownership.

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



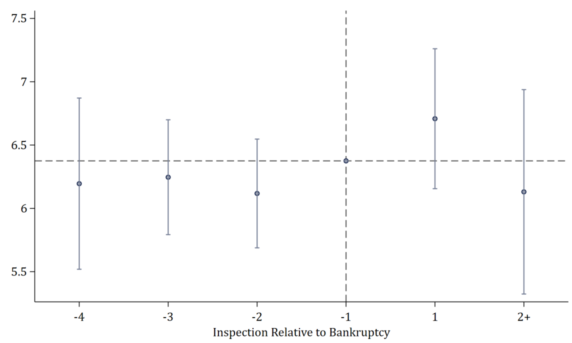
Note. This figure shows the CDF of days since leveraged buyout (LBO) for bankruptcy-filing facilities in the sample, for LBOs within ten years (3,650 days) of the bankruptcy date. Data on private equity ownership of nursing homes is from Gandhi, Song, and Upadrashta (2022).

E Supplemental Health Inspections Analysis

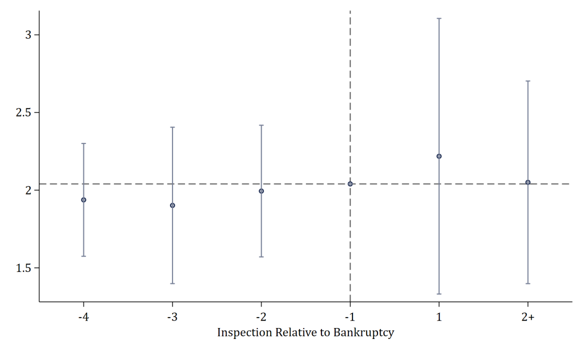
E.1 Event Studies

Figure E1 provides event study plots corresponding to Table 4. The estimates are noisy.

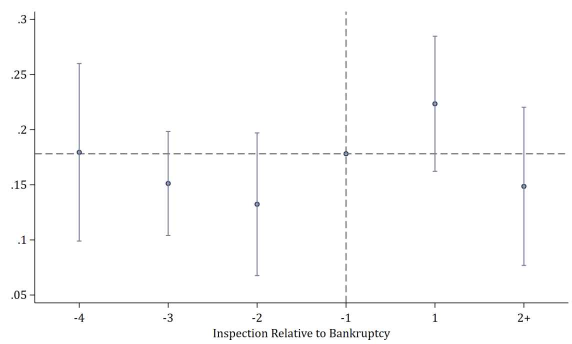
Figure E1: Provider Bankruptcy and Performance on Health Inspections: Event Studies



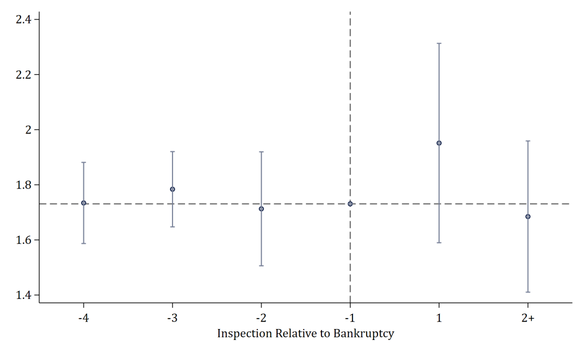
(a) Standard Deficiencies



(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 4 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 examines the impact of a bankruptcy filing on the severity and scope of health inspection violations. In the short term, there is a significant increase in isolated incidents with the potential for actual harm.

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

Panel (A). Scope of Deficiencies

	Isolated	Pattern	Widespread
Short-Term Effect	0.960**	0.082	0.011
	(0.432)	(0.200)	(0.121)
Long-Term Effect	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
Short-Term Effect	-0.001	1.015*	0.040
	(0.030)	(0.568)	(0.086)
Long-Term Effect	-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 presents our estimates of the effect of bankruptcy filings separately for each of the citations that CMS categorizes as related to nursing services. We estimate sizable statistically significant effects for three specific citations. The first is citation for staffing being insufficient to provide adequate care. Importantly, this determination is not a mechanical function of staffing hours and is instead a subjective determination made by the inspector based on their observations. In context of our previous findings that bankruptcies increase turnover but do not meaningfully reduce staffing levels or the composition of staff certifications, the increase in citations for insufficient staffing suggests that performance by new hires is substantially worse than the tenured staff they replace.[33] The second citation where we find significant effects is for failing to provide performance reviews and in-service training for CNAs. CNA certification can be obtained in as little as a month, making in-service training and evaluation a particularly important factor affecting the quality of CNA care (Trinkoff et al., 2017). High turnover might plausibly make compliance with training requirements more burdensome, as the facility has a greater number of new staff requiring training and evaluation while having fewer tenured staff able to provide training and evaluation. The last citation is for failing to post staffing levels and 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.

[33] It may also be that retained staff are less effective after the bankruptcy. This could occur if retained staff are disgruntled or are otherwise less willing or able to perform their roles effectively after the bankruptcy.

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
Short-Term Effect	0.026*	0.004	0.001	0.016**	0.034***
	(0.015)	(0.016)	(0.008)	(0.007)	(0.010)
Long-Term Effect	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 presents our estimates of the effect of bankruptcy filings separately for each of the citations that CMS categorizes as related to quality of care. Almost all of the point estimates are consistent with bankruptcy increasing citations for poor quality of care in the short-term. However, the vast majority of the estimates are imprecisely estimated. Just two stand out as statistically significant. The first is for unnecessary tube feeding or otherwise failing to provide services that would allow a tube-fed resident to return to oral feeding. Tube feeding frequently contravenes clinical recommendations (Mitchell et al., 2016) but persists because it saves money and staff time (Mitchell et al., 2004). The second is for inappropriate or unnecessary use of bedrails, which risk entrapping a resident in their bed. Consistent with this inappropriate use of bedrails, we find in Section 6.2 that recently bankrupt facilities are more likely to physically restrain residents. This is often considered a form of abuse (Lindbloom et al., 2007; Tolson and Morley, 2012) used for the convenience of inexperienced, incompetent, or overburdened staff.

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
Short-Term Effect	0.043	0.009	0.036	-0.001	0.005
	(0.033)	(0.008)	(0.030)	(0.012)	(0.011)
Long-Term Effect	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
Short-Term Effect	0.063	0.009	0.002	0.022	0.030*
	(0.043)	(0.014)	(0.010)	(0.017)	(0.018)
Long-Term Effect	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
Short-Term Effect	0.013	0.030	-0.001	0.002	0.007	0.077**
	(0.015)	(0.025)	(0.010)	(0.047)	(0.056)	(0.038)
Long-Term Effect	-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 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)

	Treated Facilities	Control Facilities	|Diff|/SD
Match Variables			
Certified Beds	122.43	124.85	0.05
	(39.42)	(48.78)	
Occupancy Rate	79.24	78.75	0.03
	(14.76)	(14.72)	
Percent Medicare	14.34	14.22	0.01
	(9.80)	(10.76)	
Employment Outcomes (Weekly; Per 100 Beds)			
Hires	1.45	1.28	0.10*
	(1.89)	(1.78)	
Separations	1.31	1.23	0.03
	(1.56)	(2.55)	
Hours			
All Workers	1975.87	1982.99	0.01
	(503.03)	(623.65)	
$\geq$ 60 Days Tenure	1374.22	1365.80	0.01
	(683.80)	(770.49)	
$<$ 60 Days Tenure	601.65	617.20	0.02
	(546.79)	(624.81)	
Percent of Hours			
$\geq$ 60 Days Tenure	68.46	67.37	0.04
	(28.57)	(30.70)	
$<$ 60 Days Tenure	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 Occupancy, Staffing Levels, and Skill Mix (Alternative Match)

	Resident-Days	Hours	Employees	RN Hour Share	LPN Hour Share	CNA Hour Share
Short-Term Effect	-5.319	-12.276	-0.292	0.210	-0.129	-0.081
	(4.868)	(9.970)	(0.333)	(0.256)	(0.166)	(0.156)
Long-Term Effect	-5.915*	-44.114***	-1.272***	-0.038	0.165	-0.127
	(3.017)	(16.912)	(0.469)	(0.497)	(0.345)	(0.219)
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	0.75	0.79	0.69
Mean	677.35	2,002.60	61.37	15.94	24.33	59.72
Observations	470,909	483,032	483,032	483,032	483,032	483,032

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. Each observation is a facility-week. Standard errors are in parentheses and clustered by nursing home chain. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

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

	Separations	Hires	High Tenure	Low Tenure
Short-Term Effect	0.147***	0.114***	-1.120***	0.922***
	(0.035)	(0.043)	(0.431)	(0.308)
Long-Term Effect	0.122***	0.152**	-3.056***	1.812***
	(0.041)	(0.064)	(0.453)	(0.651)
FE: Facility	Yes	Yes	Yes	Yes
FE: Week × Cohort	Yes	Yes	Yes	Yes
R^2	0.42	0.36	0.87	0.63
Mean	1.41	1.34	47.52	14.07
Observations	430,722	430,722	430,722	430,722

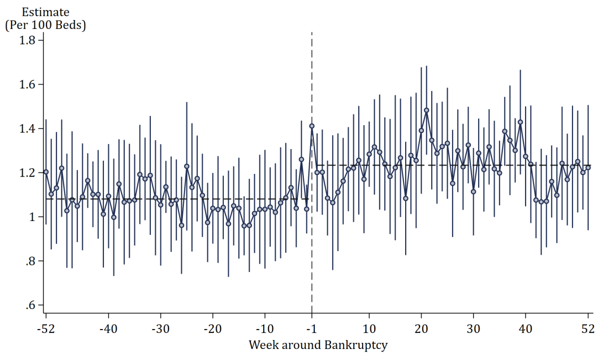
Note. This table examines staffing by high-tenure and low-tenure workers. The dependent variable "Separations" represents the number of departing workers in a facility-week per 100 beds. The dependent variable "Hires" represents the number of new workers in a facility-week per 100 beds. The dependent variables in the third and fourth columns are the number of high-tenure or low-tenure employees per 100 beds, respectively. Each observation is a facility week. Standard errors are in parentheses and are clustered by nursing home chain. See Figure F1 for event studies. We indicate statistical significance at the 10%, 5%, and 1% level using *, **, and ***, respectively.

Table F4: Performance on Health Inspections After Bankruptcy (Alternative Match)

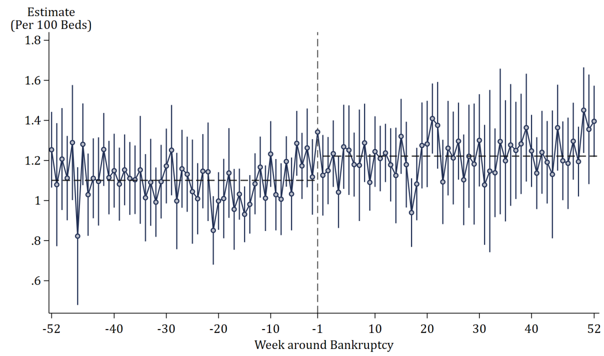
	Standard Deficiencies	Complaint Deficiencies	Nursing Services Violations	Quality of Care Violations
Short-Term Effect	0.605	0.211	0.072*	0.209
	(0.457)	(0.257)	(0.040)	(0.150)
Long-Term Effect	0.131	0.091	-0.011	0.007
	(0.548)	(0.261)	(0.030)	(0.140)
FE: Facility	Yes	Yes	Yes	Yes
FE: Event-Time × Cohort	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. Significance at the 10%, 5%, and 1% level are indicated using *, **, and ***, respectively.

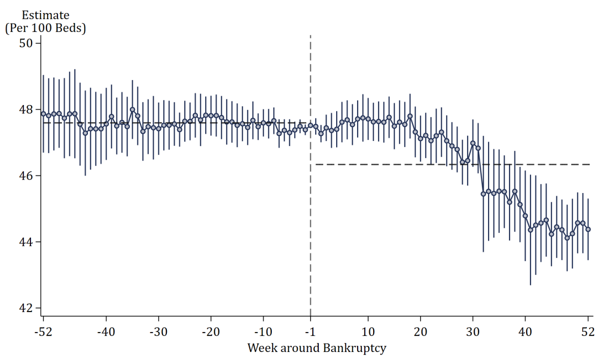
Figure F1: Dynamic Effects of Bankruptcy on Nursing Staff Tenure (Alternative Match)



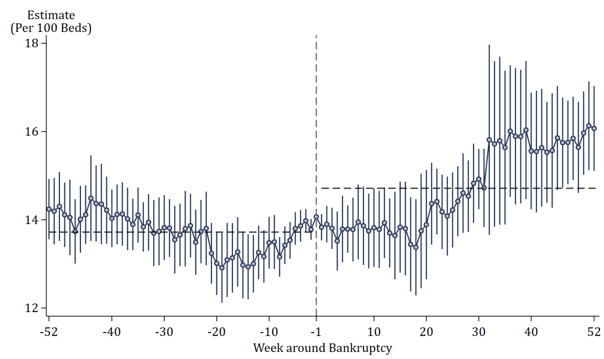
(a) Separations



(b) Hires



(c) High-Tenure Workers



(d) Low-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 separating from the facility per 100 beds. In panel (b), the dependent variable is the number of workers joining the facility per 100 beds. In panel (c), the dependent variable is the number of workers who have worked at least 60 shifts at the facility (High-Tenure Workers) per 100 beds. In panel (d), the dependent variable is the number of workers who have worked fewer than 60 shifts at the facility (Low-Tenure 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 F3 for point estimates.

G Supplemental Health Outcomes Analysis

G.1 Demand Estimates

Table G1 presents the results from estimating our distance based demand model. Patients dislike facilities that are far from their homes.

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

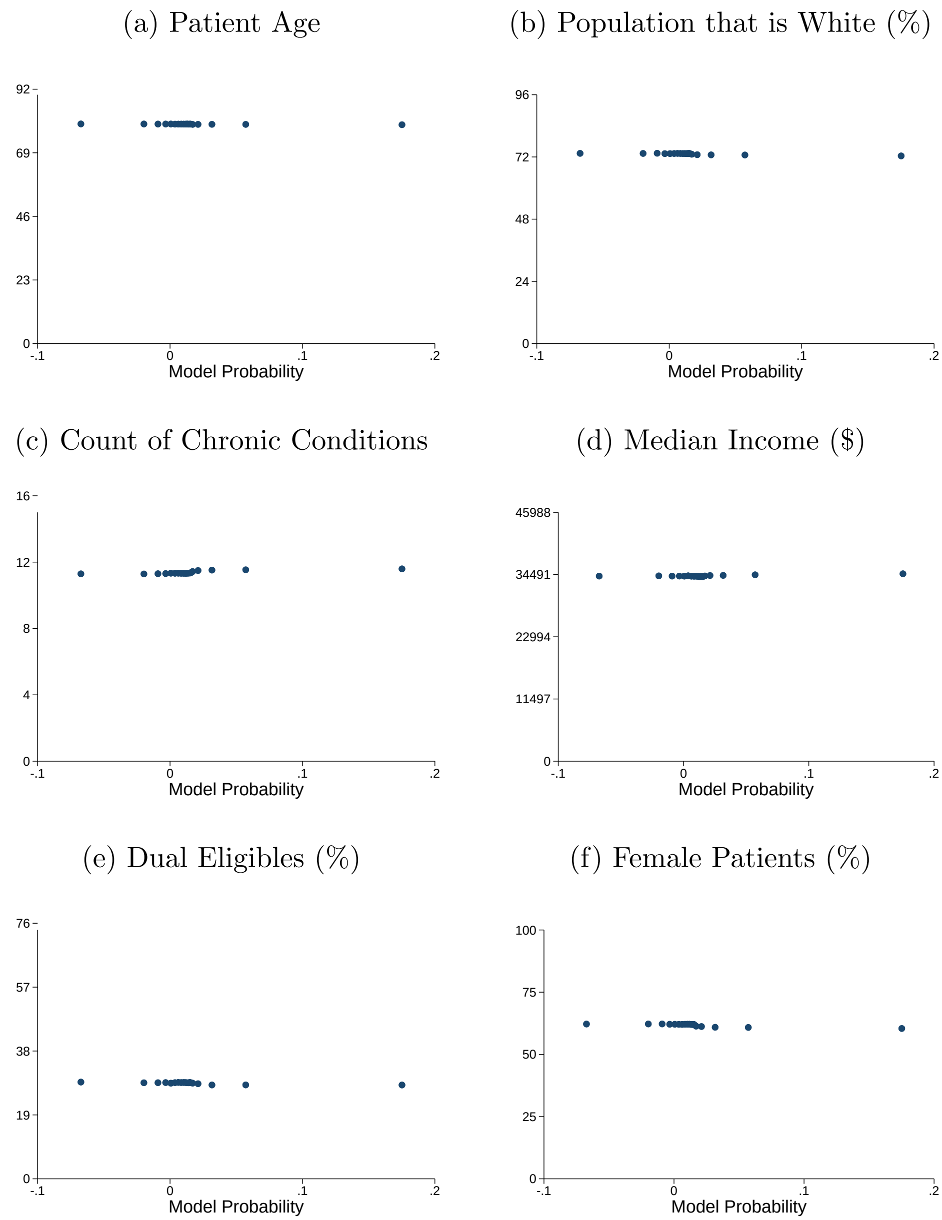
	Admission
Miles to Provider	-0.46
	(0.00025)
(Miles to Provider)^2	0.0087
	(0.000014)
N	722054502

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 5 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 5 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 5 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 5 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 5 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 5 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 5 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 5 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 5 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 (bedsores), 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.[34] We implement our instrumental variables approach via two-staged least squares:

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

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

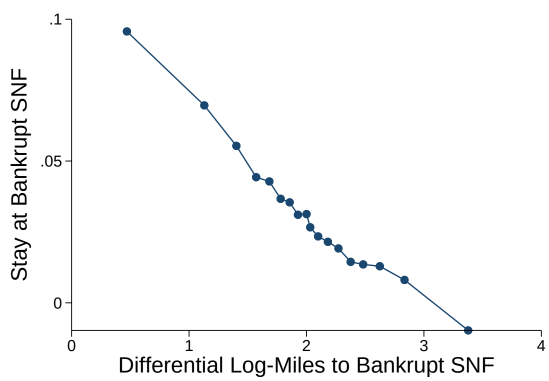
where $B_{f(i)t(i)}$ is an indicator for whether $f(i)$ filed for bankruptcy within three years prior to $t(i)$, and Y_i is a health outcome. The terms ρ, η, and α respectively represent facility, ZIP code, and time fixed effects. Finally, X_i contains a host of other health and demographic controls, 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.

[34] 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 3b, 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 3b for details.

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

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 5 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 5 for details.