Overbilling and Killing? An Examination of the Skilled Nursing Industry *

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ABSTRACT

Skilled Nursing Facility (SNF) systems that provided excess rehab therapy just above revenue thresholds quickly begin upcoding previously unidentified comorbidities under the new PDPM billing regime. Patients at these opportunistic systems develop more than 50% greater preventable conditions and have twice as many verified reviews indicating abuse. Opportunistic systems mask adverse outcomes through underreporting to CMS. Instrumental variable estimates indicate that opportunistic SNF systems are responsible for an additional 35,000 hospitalizations and 30,000 deaths since PDPM was enacted, while overbilling Medicare $4.3 billion. Opportunistic SNF systems are spreading with more than 2.5 times the acquisition rate of accurate billing systems.

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Medicare spending increased from $5,844 per beneficiary in 2000 to more than $15,727 by 2022, a rate of 4.6% per year and nearly twice the rate of inflation, and now represents more than 12% of total federal spending.[1] Yet, there is widespread concern that funding levels are insufficient and may contribute to understaffing, poor care, abuse, and neglect.[2] Although Medicare reimburses providers at fixed rates, we find that some skilled nursing systems extract more than 40% more per patient with similar diagnoses for care. Do skilled nursing facilities use these additional funds to deliver better care to the more than 1.45 million elderly individuals visiting skilled nursing facilities each year?

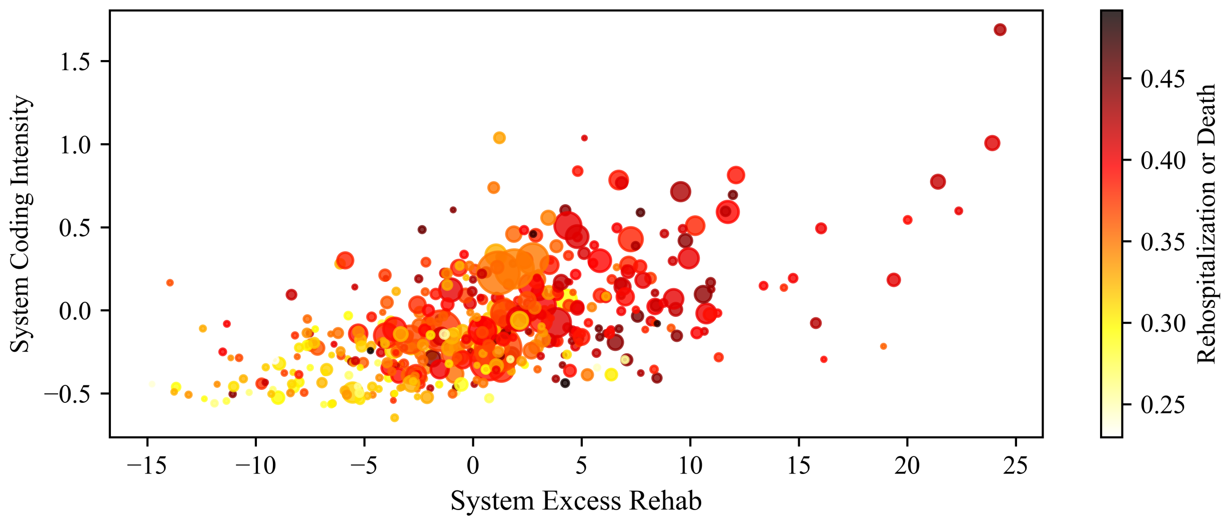
We first document widespread differences in rehab therapy provision across skilled nursing systems from January 2016 to September 2019 that are not explained by observable patient characteristics. Consistent with differences driven by financial incentives rather than patient need, variation in therapy provision levels across SNF systems is driven largely by the strategic provision of therapy minutes just above arbitrary minimum reimbursement thresholds. SNF systems providing the highest tercile of excess rehab, which we refer to as opportunistic systems, are 5.28 times more likely to deliver weekly therapy in a ten-minute window immediately above the highest reimbursement threshold than the entire 210-minute range directly below.

Citing concerns of perverse incentives and excessive rehab, CMS, which administers Medicare, introduced the Patient Driven Patient Model (PDPM) case-mix classification effective October 1, 2019. PDPM was intended to redirect funding from patients receiving intensive therapy to clinically complex patients by basing reimbursement on patient characteristics and comorbidities rather than therapy levels. We construct a measure of potential 'upcoding' using system-level intensity of high-reimbursement codes beyond what is explained by observable patient characteristics and diagnoses at the referring hospital. Contrary to CMS and industry projections, Figure 1 shows a strong correlation of 0.59 between system-level excess rehab from January 2016 to September 2019 (on the x-axis) and coding intensity from October 2019 to December 2022 (on the y-axis) despite the two regimes rewarding drasti-

[1] https://www.cms.gov/oact/tr/2023, https://www.pgpf.org/budget-basics/medicare.

[2] https://www.wsj.com/health/nursing-homes-must-boost-staffing-under-first-ever-national-standards-66328d5d, https://news.bloomberglaw.com/health-law-and-business/workforce-funding-issues-complicate-nursing-home-staffing-push.

Figure 1. Excess Rehab and PDPM Coding Intensity by System



Notes: This figure displays the relationship between system excess rehab during the RUG-IV billing era and system-level coding intensity during the Patient Driven Payment Model (PDPM) era. RUG-IV includes claims from January 1, 2016 to September 30, 2019. PDPM includes claims from October 1, 2019 to December 31, 2022. System excess rehab or coding intensity are computed as system fixed effects using Equation 1. To ensure fixed effects are precisely estimated, only systems with at least 5,000 patients are included in the figure. The color corresponds to the proportion of patients who are hospitalized within 30 days or die within 90 days. Size corresponds to the number of patients at each system.

cally different patient characteristics. The figure also shows that patients at these systems experience higher levels of death or rehospitalization.

Systems might have higher levels of coding intensity because they treat sicker patients, are better at (correctly) identifying underlying patient comorbidities, or are aggressively but incorrectly coding patients. We distinguish between these possibilities. First, differences in the highest-compensating comorbidities are extremely similar across SNF systems prior to October 2019, but increase rapidly for opportunistic systems precisely when PDPM is enacted. Second, inconsistent with the selection of sicker patients, no increase in these same comorbidities is reported at the referring hospital stay immediately preceding the SNF visit. Third, use of the highest-compensating patient codes increases significantly following acquisitions by opportunistic SNF systems despite no changes in patient characteristics. Fourth, we utilize an instrumental variables approach to capture instances in which patients are likely to be admitted to a particular SNF because other facilities in the local geographic area have limited capacity. Patients admitted under quasi-random assignment are billed at nearly identical rates to non-randomly assigned patients. Finally, 40% of patients in opportunistic systems who were receiving intensive rehab at the time of the billing transition, who would be expected to have at least moderate physical function to handle intensive rehab, are subsequently coded as having limited or even very low physical function with serious comorbidities under PDPM.[3] Differences in captured revenue for opportunistic systems are significant—as much as $6,000 per patient ($20,000 vs. $14,000) despite similar patient characteristics.

Do opportunistic systems use the additional revenue to provide better patient care? Alternatively, could upcoding indicate a corporate culture that prioritizes profit extraction over patient need and cuts costs at the expense of patients? We investigate the quality of care provided by opportunistic and non-opportunistic systems through examining patient health outcomes, patient reviews, unannounced health inspections, and nurse staffing. Verified online reviews for facilities that engage in upcoding are 2.5 times more likely to indicate patient abuse or neglect—19.1% of reviews for facilities from systems in the top decile of excess rehab compared to only 7.1% of reviews in the bottom decile. Through examining cases where SNF patients are sent to the hospital immediately following the skilled nursing stay, we find that opportunistic systems mask adverse health outcomes through underreporting of pressure ulcers, urinary tract infections (UTIs), and traumatic falls facilitating inflated CMS ratings, which are posted on various websites for prospective patients. Opportunistic systems also have lower inspection ratings, more serious health deficiencies, and more substantiated resident complaints. Consistent with cost-cutting in opportunistic systems, we find significantly lower levels of nurse staffing at these facilities, with 37% fewer registered nursing hours, despite billing Medicare for greater patient acuities.

Instrumenting for patient selection using plausibly exogenous occupancy constraints, we find that patients at the most opportunistic systems are 67% more likely to develop pressure ulcers, 7.6% more likely to be re-hospitalized within 30 days, and 9.6% more likely to die within 90 days of leaving the skilled nursing facility. These estimates imply that opportunistic systems are responsible for an additional 10,200 preventable conditions, 35,000 hospitalizations, and 31,000 deaths from October 2019 to December 2022 since PDPM was

[3]Only 8% of intensive rehab patients are billed with the same levels of function at low excess rehab systems.

enacted.

Do opportunistic SNF systems face discipline for poor care through reputational damage or regulatory pressure? Although single-payer systems such as Medicare set fixed prices, providers should still compete on quality. Yet, significant informational asymmetries exacerbated by a lack of data on health outcomes and strong preferences for local care could hinder market discipline. If market and external discipline are sufficiently weak, some providers may focus on rent extraction through maximizing reimbursement and minimizing costs. Consistent with weak reputational costs, opportunistic systems have similar patient retention. While CMS guidelines encourage regulators to consider quality of care when approving acquisitions, opportunistic systems have expanded at over 2.5 times the rate of non-opportunistic systems, suggesting that the profitability of intense use of high-reimbursement codes and reduced staffing combined with light regulatory screening of mergers fuels the expansion of these SNF systems.

There are several implications from our study. First, there is a strong system fixed effect related to excess billing practices (under two regimes of reimbursement) and poor quality of care indicating strategic decisions by SNF management rather than geography or doctor decisions. Second, despite PDPM being designed to stop wasteful and unnecessary Medicare spending, SNF systems quickly gamed the new payment structure demonstrating that changes in reimbursement design alone are unlikely to be successful. Third, although the most opportunistic systems are billing 40% more per patient, generating excess Medicare costs of more than $1.33 billion per year, patients at such systems receive reduced nurse staffing and increased health deficiencies. Fourth, underreporting of adverse health outcomes by opportunistic SNF systems results in misleading CMS quality ratings and indicates that more robust summary measures of quality of care are needed for patients and their family members. Fifth, the fact that opportunistic systems, which underinvest in staffing and care, are increasing rapidly through acquisitions indicates a spread of poor health outcomes. Considerably tougher penalties, including criminal ramifications, may be needed to change longstanding norms.

1 Literature Review and Skilled Nursing Facility Background

1.1 Related Research

Our paper relates to several strands of literature. First, there is a literature examining the practice of potentially false or unnecessary billing practices. Hospital upcoding has been shown in a variety of settings (Silverman and Skinner, 2004; Dafny, 2005; Heese et al., 2015; Bastani et al., 2019; Joiner et al., 2024; Geruso and Layton, 2020) using different methods including machine learning (Shekhar et al., 2023). O'Malley et al. (2021) find that home healthcare fraud spreads through networks. Bowblis and Brunt (2014) find evidence that SNFs provide additional therapy to increase revenue,[4] but no evidence of upcoding physical function scores. Our paper provides an examination of billing and health outcomes under two regimes in skilled nursing.

Second, a literature explores the implications of billing practices and investment in quality of care. League (2022) finds that firms respond to increasing Medicare denial rates for physician services by consolidating into larger groups and increasing investment in billing technology. Internal firm organization and incentives (Gaynor et al., 2004; Clemens and Gottlieb, 2014) as well as vertical organizational structure with related entities (Geruso and Layton, 2020) have been shown to affect healthcare billing. Dafny (2005) finds that hospitals utilize increased revenue from upcoding highly compensating diagnoses in the provision of care across all patients. Cooper et al. (2022) find hospitals that charge higher prices deliver better care to patients, but only in competitive markets. He et al. (2020) find that a regulatory shock that increased Medicare reimbursement resulted in longer skilled nursing stays. Blegen et al. (1998); Tong (2011); Friedrich and Hackmann (2021) find that reductions in nursing investment predict adverse patient health outcomes including death. This paper studies the relationship between upcoding and cost-cutting measures such as reduced nurse staffing.

Third, there is a literature linking ownership structure and concentration to outcomes. Eliason et al. (2020) finds that dialysis chains transfer billing and cost-cutting strategies

[4] Bowblis et al. (2016) find that this activity is more prevalent at for-profit facilities and Temkin-Greener et al. (2019) find that Ultra-High therapy on the day of death is more present in for-profit New York nursing homes than in non-profit nursing homes. The Office of the Inspector General (OIG) found that as many as 22% of claims were billed for therapy levels that were higher than could be supported by medical records (Levinson and General, 2014).

through acquisitions and that these generally have adverse effects on patients. Gupta et al. (2023) find that private-equity acquired nursing homes reduce staffing and experience overall increased mortality. Braun et al. (2020) find that PE-owned skilled nursing facilities had fewer resources for COVID-19. Liu (2022) finds that private equity acquisitions in hospitals increased insurance claim prices by 11%.[5] Such findings have prompted regulatory action from state and federal governments aimed at subjecting private equity transactions to additional scrutiny.[6] Ownership concentration has been linked to increased prices by hospitals (Gaynor and Town, 2011), health insurance providers (Dafny et al., 2012), and strategic supply reduction more generally at the costs of taxpayers (Doraszelski et al., 2024).[7] We find that ownership structure is important with opportunistic facilities expanding at considerably faster rates, however, the focus on private equity ownership appears too narrow as most opportunistic systems do not appear to be linked to private equity.

Finally, there is a growing literature examining methods of preventing fraud and abuse. Howard and McCarthy (2021) examine DOJ investigations and find deterrence effects ten times the amount of prosecuted fraud. Gandhi and Olenski (2024) use detailed data from Illinois to show how SNFs tunnel funds through related management and real estate entities to shield SNFs against lawsuits. Shi (2023) shows that Medicare's Recovery Audit Contractor (RAC) Program generates more than 24 times the cost in future savings. Through the staggered adoption of regulatory changes in ambulance visits across states from 2003 to 2017, Eliason et al. (2021) find that these administrative changes are much more effective than enforcement. Since the October 2019 administrative change to SNF billing seems to have been largely ineffective, our results highlight that not all administrate changes are effective and these tools may need to be coupled with tougher auditing and enforcement to prevent fraud and abuse.

[5]Studies have generally found robust evidence that PE ownership in healthcare increases prices in a variety of healthcare settings, while evidence of quality of care has been more mixed (Howell and Liu, 2023).

[6]States that have passed such laws include Oregon, California, New York, Illinois, and Minnesota. For additional information, see `https://www.dlapiper.com/en/insights/publications/2024/01/us-government-targets-healthcare-private-equity-top-points-for-risk-management`.

[7]There is a growing literature finding that differences in organizational culture and practices explain financial maleficence in a variety of contexts including financial advisor misconduct (Egan et al., 2019; Dimmock et al., 2018), residential and commercial mortgage fraud (Piskorski et al., 2015; Griffin and Priest, 2023), and pandemic loan fraud (Griffin et al., 2023). Bertuzzi et al. (2023) find that dialysis centers may drop sicker patients to improve their quality scores.

1.2 Skilled Nursing Facilities

Skilled nursing facilities (SNFs) are designed to provide nursing and rehabilitation services and are typically used for additional rehabilitation and therapy following an inpatient hospital stay. To be eligible for Medicare coverage, a patient must enter the skilled nursing facility within 30 days of a qualifying three-day minimum hospital stay, and the stay must be related to the hospitalization. Medicare Part A covers skilled nursing care for up to 100 days per qualifying inpatient stay.

Reimbursement for skilled nursing under RUG-IV was largely based on the total therapy minutes provided. Patients were classified into one of five distinct payment groups based on the minutes of therapy services delivered per week leading to considerable incentives to increase therapy.[8] Despite largely unchanged patient characteristics, the proportion of patients billed for Ultra-High therapy rose from 17% in 2006 to more than 53.7% by 2019.[9] Skilled nursing facilities are incentivized to provide just enough care to achieve the highest paying case-mixes. To illustrate, a patient that receives 715-719 minutes of therapy in a week qualifies for Very High rehab; while a patient receiving 720 minutes of therapy qualifies for Ultra-High rehab, which can increase reimbursements by more than $100 per day. Alternatively, if facilities choose therapy levels to maximize revenue, we expect that patients would be provided with just enough therapy to qualify for a given level of billing. CMS has stated that "the increase in 'thresholding'... is a strong indication of service provision predicated on financial considerations rather than resident need."[10]

[8] The classifications are Low (45-149 minutes), Medium (150-324 minutes), High (325-499 minutes), Very High (500-719 minutes) and Ultra (720+ minutes). In 2018 daily reimbursement rates for patients at a medium level of therapy ranged from $320.28-$616.13 per day depending on the services provided, but a patient receiving Ultra-High therapy would be eligible for reimbursements of $527.97—$832.89 per day. https://www.govinfo.gov/content/pkg/FR-2018-08-08/pdf/2018-16570.pdf

[9] https://oig.hhs.gov/oei/reports/oei-02-09-00202.pdf Substantial concerns were raised that RUG-IV reimbursement resulted in patients receiving unnecessary care and being "rehabbed to death" (Flint et al., 2019).

[10] https://www.govinfo.gov/content/pkg/FR-2018-05-08/html/2018-09015.htm and that the amount of therapy that is right over the required 720 minutes "is too significant to be an accurate reflection of... population individualized needs." https://www.cms.gov/Outreach-and-Education/Outreach/NPC/Downloads/2018-12-11-PPS-Transcript.pdf

1.3 Patient Driven Payment Model (PDPM)

With the intent of changing incentives to tailor care to individual patient needs, CMS replaced RUG-IV with the Patient Driven Patient Model (PDPM) effective October 1, 2019.[11] Reimbursements under PDPM are based on five patient components: Nursing, Physical Therapy ("PT"), Occupational Therapy ("OT"), Speech-Language Pathology ("SLP"), and Non-Therapy Ancillary Services ("NTA"). Each component has corresponding case-mix groups based on a patient's primary diagnosis, physical or cognitive status, and secondary conditions such as depression or other comorbidities determined by the skilled nursing facility. Case-mixes that typically require higher levels of care are awarded higher levels of reimbursement. An SNF receives greater revenue when it codes patients as having greater comorbidities leading to incentives to exaggerate patient conditions. Because reimbursement rates typically vary the most within the Nursing and SLP components, we focus attention on billing within these components.[12]

1.3.1 Nursing Component

The reimbursement rate of the Nursing component of PDPM is determined by a patient's underlying diagnosis, intensity of services needed, physical function score, and depression status as demonstrated in Exhibit 1.[13] Daily reimbursements for the Nursing component (in 2022) range widely from $68.28 to $420.05. Within the Nursing component, we investigate three major categorizations that can move a claim to higher levels of reimbursement: Special Care High primary diagnosis, depression, or assignment to the lowest category of physical function. These categories were chosen as candidate upcodes because they are determined largely by internal staff assessment, may be difficult to externally verify, and provide the largest reimbursement increases.

1.3.2 SLP Component

The Speech Language Pathology (SLP) component of reimbursement features 12 case-mix indices with daily reimbursement rates ranging from $15.06 to $93.25 per day (as demonstrated in Exhibit 2). Patients are screened for having an Acute Neurologic primary diagnosis, additional SLP-related comorbidities, and cognitive impairment with reimbursement

[11] https://www.cms.gov/medicare/medicare-fee-for-service-payment/snfpps/downloads/pdpm_faq_final_v5.zip

[12] The NTA case-mix depends to a larger extent on verifiable patient conditions rather than staff assessment and so may be more difficult to manipulate. Nonetheless, we examine potential shifts in NTA-related coding intensity in Section 4.1.

[13] Additional details can be found in Appendix 9.1.

increasing in the count of such conditions. We investigate the use of these patient codes and focus on claims that have at least two of the three conditions.[14] Patients are then assessed for requirement of a mechanically altered diet or swallowing disorders. Patients with both conditions reach the highest billing category.[15]

2 Data and Summary Statistics

The primary data for this study is the Skilled Nursing Facility Limited Data Set, which covers the universe of Medicare Skilled Nursing claims from January 1, 2016, to December 31, 2022. The second major dataset used is the Inpatient Limited Data Set which contains inpatient hospital visits, diagnoses, and procedures. Both datasets are compiled and distributed by the Centers for Medicare and Medicaid Service (CMS). The Inpatient and Skilled Nursing datasets share an anonymized beneficiary ID that captures patient characteristics and health history prior to a SNF visit as well as future hospitalizations, SNF stays, and some health outcomes for patients. Key variables in the skilled nursing data include the patient's primary diagnosis and up to 24 secondary diagnoses, patient therapy level (RUG-IV) or case-mix (PDPM), patient age in five-year increments, race, gender, county, and number of treatment days. The inpatient data contains the same patient characteristics, as well as diagnoses or procedures documented at the hospital. The data covers a total of 14,318,809 skilled nursing stays from 7,287,257 unique patients.[16] To track patient mortality following SNF stays, we additionally make use of the Hospice Limited Data Set.

We also utilize several other databases. Skilled Nursing Facility Enrollments from CMS Public Use Files (PUF) are used to classify facilities into systems. Facilities are considered part of the same system if they share an Affiliation ID. 9,682 of the 16,744 (58.9%) facilities that treat 66.0% of patients are identified as belonging to an SNF system. CMS affiliated entity status may not reflect every possible SNF system due to the complex nature of possible ownership structures as well as a reliance on ownership data being accurately submitted.[17] Because of our focus on practices that can be identified more precisely with systems, independently operated facilities are not considered in our main analysis, however, we examine

[14] For simplicity of exposition, we refer to these case-mix indices as "SLP High".

[15] SLP case-mixes are described in further detail in Appendix 9.2.

[16] Our dataset excludes long-stay residents which are typically paid for by Medicaid, and account for approximately 60% of all nursing home patient-days (Gupta et al., 2023).

[17] For technical methodology about how CMS identifies SNF affiliations, see https://data.cms.gov/resources/nursing-home-affiliated-entity-performance-measures-methodology.

billing practices for all facilities in Section 7.2. The CMS Change of Ownership (CHOW) is used to identify acquisitions. Additional facility-level information including occupancy, staffing, and proportion of assessments billed just above the Very-High (500-509 minutes) and Ultra-High (720-729 minutes) thresholds comes from facility-level CMS Public Use Files. Clinical Classification Software Refined (CCSR) from the Healthcare Cost and Utilization Project (HCUP) is used to classify similar diagnosis and procedure codes.

We obtain patient reviews of skilled nursing facilities from Caring.com, an online senior care website that provides information and hosts nursing home reviews. The Terms of Use for Caring.com require reviewers to have an account, have firsthand experience within three years of review submission, provide valid contact information, and disclose that they do not have any known conflicts of interest.[18] In total, we gather 73,237 reviews of which 64,382 are linked to a specific skilled nursing facility. The reviews contain descriptive text as well as an overall star from one (worst) to five (best).

3 Is There a Relation Between System-level Excessive Rehab in the RUG-IV Era and Upcoding in PDPM?

We first wish to examine SNF systems engaged in providing excessive rehab during RUG-IV. Next, we investigate whether systems that engaged in potentially excessive rehab billing in the RUG-IV era also code patients more intensely in the PDPM era. In the next section, we then investigate whether this relationship can be explained by observable or unobservable patient characteristics, patient selection, or upcoding.

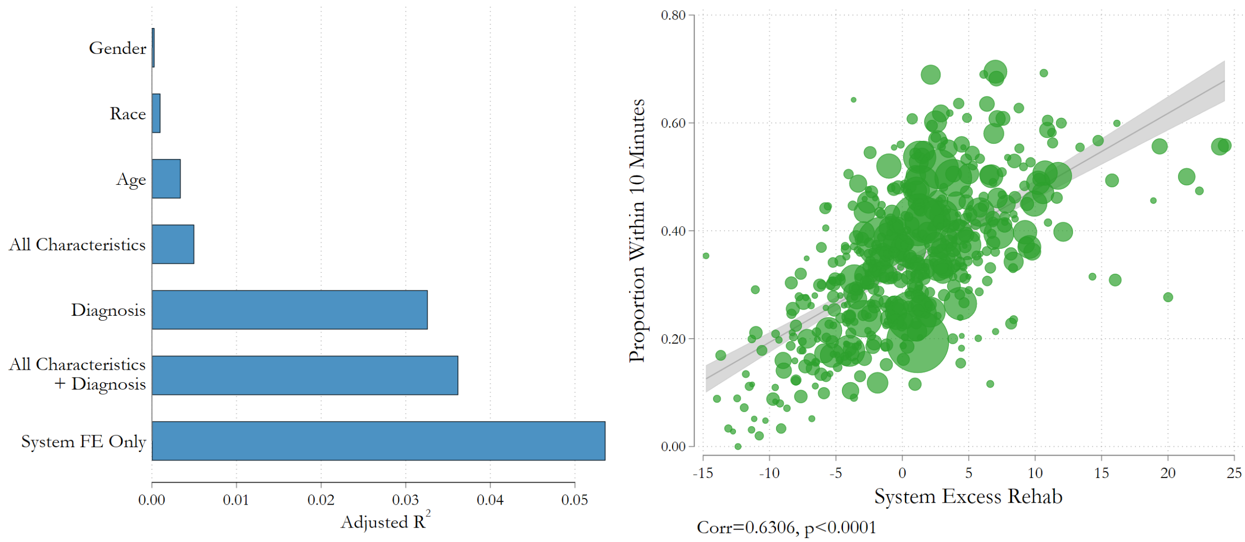
3.1 Do Some SNF Systems Provide Excessive Levels of Rehab?

We examine whether SNF systems differ along the intensity of rehab therapy by measuring the number of days that patients are billed for Ultra-High therapy, the highest-compensating and most intense case-mix. Appropriate rehab for a patient may largely depend on patient characteristics, so we control for gender, age, race, and primary diagnosis documented at the referring hospital. We then estimate a regression of the form:

$$UltraRehabDays_{ijt} = \alpha + \theta X_i + FixedEffects + \sum_{j=1}^{J} \beta_j System_j \epsilon \tag{1}$$

[18]For additional details, see https://www.caring.com/about/review_guidelines/. All reviews meeting guidelines are published, and a facility cannot pay to have reviews removed.

Figure 2. Importance of SNF System in Rehab



Notes: This figure explores the importance of the SNF system in explaining variation in Ultra-High rehab. Patient characteristics include Gender, Race, and Age. Diagnosis is a patient's inpatient diagnosis at the CCSR-level. The right subgraph is a scatterplot with a SNF system's excess rehab as determined by Equation 1 on the x-axis and the proportion of SNF claims billed for between 720-729 minutes of weekly therapy. The size of the bubbles denotes the number of patients at each system.

where $UltraRehabDays_{ijt}$ is the number of Ultra-High rehab days that patient i receives at SNF system j during quarter t. The system fixed effect captures the average number of days of Ultra-High rehab a patient receives at a SNF system in excess of what can be explained by observable patient characteristics and diagnosis at the referring hospital.[19] We refer to this fixed effect, β_j, as system excess rehab. We find widespread differences with system fixed effects ranging from -13.76 days to 24.27 days implying drastically different levels of Ultra-High rehab for patients with similar observable conditions at different SNF systems.[20] How important is the SNF system in explaining variation in the provision of rehab? Figure 2 plots the adjusted R^2 for OLS regressions with fixed effects for patient characteristics, inpatient diagnosis, and SNF system. System fixed effects explain greater variation in days of Ultra High rehab than all patient characteristics and diagnosis combined.

Large differences in the provision of intensive rehab therapy at SNF systems could result

[19]We choose to use a patient's primary diagnosis at the referring hospital as the main control specification because diagnoses at the SNF may be influenced by the system.

[20]For reference, the median (mean) number of days of Ultra-High rehab a patient receives during RUG-IV is 12 (15.61) days as shown in Table IA.I. To allow for precise estimates of system fixed effects, only facilities with at least 1,000 stays are included in the range referenced above.

from heterogeneous patient needs. While patients visiting facilities with greater Ultra-High rehab could have greater rehab needs on average, there is no reason to expect provision of care to bunch around arbitrary thresholds. Alternatively, if differences in utilization of Ultra-High rehab across SNF systems reflects willingness to provide excessive and unnecessary care, facilities should provide just enough care to qualify for the increased level of billing. We find that most variation in system fixed effects is related to billing which occurs just above the 720-minute threshold as shown in Figure 2.[21] Patients at facilities in the highest tercile of excess rehab are 5.28 times more likely to receive between 720-729 minutes of weekly therapy than the entire 210-minute range immediately below the threshold which includes alternative "round-hour" prescriptions for nine, ten, or eleven hours as well as any times between.[22] Finally, we examine instances when additional rehab therapy is unlikely to be helpful or necessary because the patient is often physically unable to perform physical activity–during the final days of a patient's life (Temkin-Greener et al., 2019). A total of 38.7% of patients who die in facilities with the highest levels of excess rehab were receiving the most-intense Ultra-High rehab up to the day of death compared to 8% for the facilities with the lowest excess rehab (Figure IA.2). Together, the abnormal levels of rehab at certain SNF systems suggests a system focus on profit extraction rather than patient outcomes.

3.2 Do SNF Systems with Prior Excess Rehab Code Patients More or Less Intensely Under PDPM?

The Patient Driven Payment Model was intended to reallocate reimbursement from patients receiving the highest levels of therapy towards patients with more complex clinical needs with CMS projecting the largest decreases for facilities with a high proportion of Ultra-High rehab residents.[23] Industry participants also generally expected that facilities providing higher levels of therapy under RUG-IV would realize reductions in revenue under

[21] The correlation between system excess rehab and the proportion of patient days billed between 720-729 minutes is 0.6306, whereas the correlation between system excess rehab and proportion of patient days billed any number of minutes above 730 is 0.1213 as shown in Panel A of Figure IA.1.

[22] Additionally, there is a strong and positive relationship between billing across the Very-High rehab threshold (500-509 weekly minutes) and Ultra-High (720-729) two thresholds (correlation coefficient of 0.812 and graphically shown in Figure IA.1, Panel B) suggests SNF systems strategically target billing thresholds, in contradiction to CMS guidance (https://www.govinfo.gov/content/pkg/FR-2017-05-04/pdf/2017-08519.pdf).

[23] https://public-inspection.federalregister.gov/2018-09015.pdf

PPDM due to fewer comorbidities among patients doing intensive rehab.[24] However, if differences in RUG-IV therapy levels primarily reflected excessive and unnecessary rehab by opportunistic SNF systems to increase revenue, then these systems might find mechanisms to increase revenue under PDPM using higher-compensating billing codes. We construct a measure of PDPM coding intensity using five billing categorizations within the SLP and Nursing which substantially increase reimbursement revenue. The categories we study are: Depression, Dietary Restriction, SLP High, Special Care High, and Low Function. We investigate billing practices within each of these categories as well as the sum of all five, which we call coding intensity. While the use of these PDPM billing codes is justified in many cases, abnormal levels of use could be an indication of upcoding. We first document substantial variation in usage of these high-revenue billing codes across SNF systems. Analysis in the following sections examines whether cross-sectional variation in the coding intensity across systems is driven by patient heterogeneity, superior diagnostics, or upcoding.

Figure 1 shows that systems with higher levels of excess rehab during the RUG-IV era subsequently experience more intense billing under the PDPM era in contrast to projections. Patients at facilities with higher excess rehab also experience higher levels of death or rehospitalization (denoted by the shade of the markers).[25]

Individual patient-level regressions also show that moving from lowest to highest tercile of system excess rehab is associated with a 25% increase in coding intensity under PDPM.[26] We further explore whether higher total coding intensity is explained by specific categories and find that SNF systems that previously had higher excess rehab demonstrate more intense PDPM billing along each of the five categories (in Table IA.II). Additionally, we find higher levels of Ultra-High rehab and PDPM coding intensity by excess rehab systems across all

[24] https://www.monterotherapyservices.com/articles/coming-soon-to-a-snf-near-you-new-payment-model/ https://www.monterotherapyservices.com/articles/coming-soon-to-a-snf-near-you-new-payment-model/

[25] The correlation between system excess rehab (from 2016 to September 2019) and adjusted coding intensity is 0.587 (p<0.001). Because PDPM case-mixes are tied to underlying patient conditions, we adjust the coding intensity measure by residualizing on observable patient characteristics utilizing Equation 1 except that the outcome variable is coding intensity.

[26] The most saturated specification produces a coefficient of 0.0244 which implies that a shift from lowest to highest tercile of system excess rehab corresponding to 10.5 days, is associated with an increase in total coding intensity of 0.256 (0.0244×10.5), 25% of the unconditional mean. Coefficients are precisely estimated with t statistics ranging from 9.51 to 12.60 (as shown in Table 1).

but a few of over 340 diagnosis groups (as shown in Figure IA.3). Finally, we examine how PDPM coding intensity has changed over time. Consistent with SNF systems learning to maximize revenue under the new regime, there has been an increase in coding intensity across all system types increasing by 0.92 to 1.06 (17.5%) from Q4 2019 to Q4 2022 with most systems experiencing an increase in coding intensity (shown in Figure IA.4).

Table 1. Excess Rehab and PDPM Billing

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with billing intensity during the Patient Driven Payment Model (PDPM) era (October 1, 2019-December 31, 2022). We estimate an OLS regression of the form:

$$CodingIntensity_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where $CodingIntensity_{ijt}$ is the sum of indicators for whether a patient is classified as Low Function, Special Care High, Depression, SLP High or Dietary Restriction and ranges from zero (least intense) to five (most intense). Patient controls include gender, age (in five-year increments), and race. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Robust standard errors are clustered at the SNF system level.

	(1) Code Intens.	(2) Code Intens.	(3) Code Intens.	(4) Code Intens.
Excess Rehab	0.0385***	0.0371***	0.0369***	0.0244***
	(12.60)	(11.98)	(12.07)	(9.51)
Quarter-Year FE	Yes	Yes	No	No
Patient Gender	No	Yes	Yes	Yes
Age Bucket	No	Yes	Yes	Yes
Patient Race	No	Yes	Yes	Yes
Diagnosis FE	No	Yes	No	No
County x Quarter FE	No	No	No	Yes
Diagnosis x Hospitalization Length	No	No	Yes	Yes
Observations	3,864,152	3,864,144	3,858,952	3,855,593
Adjusted R^2	0.038	0.114	0.114	0.159

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

4 What Explains Variation in Coding Intensity?

Systems might experience higher levels of coding intensity because they treat patients who are ex-ante more likely to qualify for high levels of reimbursement, select patients with more qualifying comorbidities, are better at (correctly) identifying underlying patient characteristics and comorbidities, or are aggressively but incorrectly coding patients.

We examine these alternative hypotheses utilizing five main tests. First, we examine the prevalence of comorbidities across facilities prior to PDPM using patient diagnoses reported throughout the sample period across facility types and utilize hospital diagnoses as an independent measure of patient comorbidities. Second, we utilize a sample of facility acquisitions to examine the change in billing practices following mergers. Third, we utilize competitor constraints to generate quasi-random patient assignment in an instrumental variables framework. Fourth, we assess potential changes in relative care and coding for patients who are already in SNFs during the transition of billing regimes. Finally, we examine changes in comorbidities for patients who switch SNF systems in a short period of time.

4.1 Patient Comorbidities Before and After PDPM

Are high levels of coding intensity from skilled nursing facilities that previously provided excessive rehab due to previous specialization in treating comorbidities with higher PDPM reimbursements? Diagnoses are recorded by skilled nursing facilities over the entire sample period, but compensation for qualifying diagnoses increases only after PDPM takes effect. If differences in coding intensity by opportunistic SNF systems result from patient specialization, then these facilities should have a higher incidence of SLP-related and NTA-related comorbidities prior to PDPM. Alternatively, if differences in coding intensity occur due to upcoding, then the estimated prevalence of highest-compensating comorbidities should increase following PDPM and increase to a greater extent in systems previously administering excess rehab.

We first examine the prevalence of patients whose primary diagnosis belongs to the Acute Neurologic clinical category over time and across facility types.[27] While CMS guidelines dictate that the primary diagnosis be "the main reason. . . a person is admitted to the SNF," facilities nonetheless have discretion in assigning patient diagnoses and are incentivized to code diagnoses resulting in higher reimbursement. The prevalence of Acute Neurologic conditions was remarkably similar across facility types prior to the introduction of PDPM—8.01% of patients at facilities in the lowest tercile of excess rehab qualify as Acute Neurologic versus 8.04% of patients at facilities belonging to opportunistic systems. However, once PDPM takes effect, Acute Neurologic diagnoses increase to 20.68% of diagnoses at opportunistic

[27] A patient is classified as having an Acute Neurologic condition if their primary diagnosis is included in the list of 2,026 ICD-10 https://www.cms.gov/medicare/payment/prospective-payment-systems/skilled-nursing-facility-snf/patient-driven-model.

facilities versus 13.44% of patients at facilities in the bottom tercile of excess rehab.

More formally, we utilize a difference-in-differences approach to estimate the relative likelihood of an Acute Neurologic primary diagnosis at opportunistic facilities versus other facilities over time. Crucially, because a patient's primary diagnosis determines eligibility for Acute Neurologic billing, we include fixed effects for a patient's primary diagnosis identified at the referring hospital immediately preceding the skilled nursing stay. Figure 3 plots coefficients from a dynamic difference-in-differences regression of the form:

$$Acute_{ijt} = \alpha + \sum_{t=1}^{T} \beta_t Period_t \times Opportunistic_j + \theta X_i + FixedEffects + \epsilon \tag{2}$$

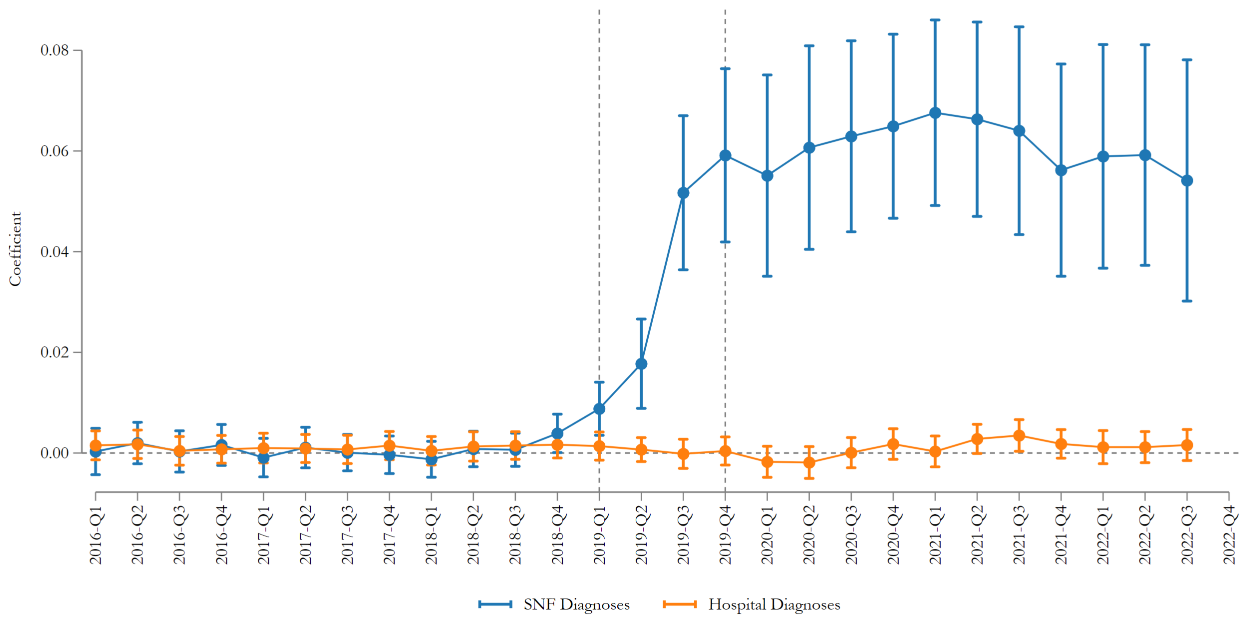
where $Acute_{ijt}$ is an indicator variable equal to one if a patient's primary diagnosis is classified as Acute Neurologic and zero otherwise. $Opportunistic_j$ is an indicator equal to one if a facility belongs to a system in the top tercile of excess rehab (opportunistic systems) and zero otherwise. $Period_t$ are indicators for each quarter-year and control for aggregate time-series variation in the likelihood of Acute Neurologic diagnoses. A facility fixed effect is included in the specification to control for time-invariant facility-level heterogeneity in the likelihood of Acute Neurologic Diagnoses. Acute Neurologic diagnoses at opportunistic systems (shown in blue) increase sharply following the implementation of PDPM and remain persistently high through the end of the sample. We further investigate the cross-sectional relationship between a system's billing practices during RUG-IV and Acute Neurologic billing (in Figure IA.5) by plotting a binscatter of Acute Neurologic against system excess rehab separately for the RUG-IV and PDPM eras. Acute Neurologic classification is increasing in excess rehab during PDPM but not during RUG-IV when the coding received no additional compensation.

Patient reimbursement also increases for comorbidities that are SLP or NTA-related (see Exhibit 2).[28] During the RUG-IV era, the prevalence of SLP-related comorbidities was extremely similar across SNF systems.[29] We plot coefficients from the dynamic difference-in-difference specification. While the incidence of SLP-related and NTA-related diagnoses

[28]Unlike Acute Neurologic, these comorbidities need not be the primary diagnosis and can be included in any of 24 secondary diagnoses.

[29]3.31% (3.11%) of patients at systems with the lowest (highest) tercile of excess rehab were recorded as having qualifying SLP-related comorbidities prior to PDPM.

Figure 3. Acute Neurologic Diagnoses Around Regime Change



Notes: Blue denotes Acute Neurologic primary diagnoses as recorded at the skilled nursing facility while orange denotes Acute Neurologic primary diagnoses as recorded at the preceding inpatient hospital stay. Coefficients are estimated using Equation 2. 95% confidence intervals for each coefficient are displayed.

was extremely similar across systems prior to PDPM, these conditions increased sharply at opportunistic systems following PDPM.

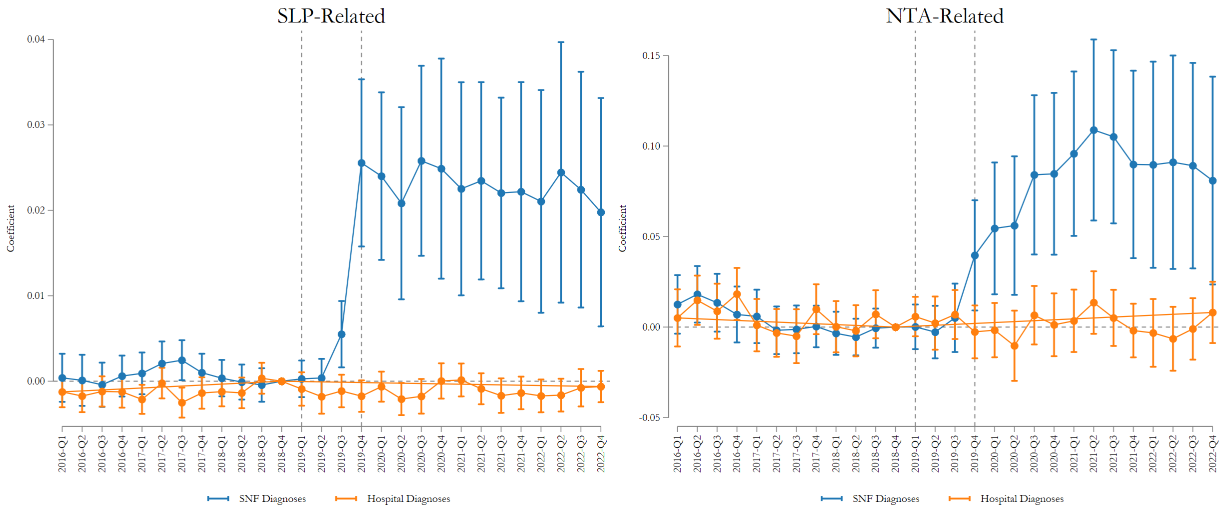
4.2 Do Opportunistic Systems Select Patients with Comorbidities?

Does PDPM induce opportunistic SNF systems to selectively admit patients with higher-compensating comorbidities? Opportunistic systems were no more likely to treat patients with Acute Neurologic, SLP-related, or NTA-related conditions prior to PDPM, implying that prior specialization does not explain observed differences in comorbidity incidence once PDPM is enacted. Nonetheless, the increased presence of highly-compensating comorbidities at opportunistic systems could arise because these systems are advantaged at attracting, selecting, and/or retaining sicker patients. We explore this possibility in detail.

4.2.1 An External Measure of Patient Health

To test whether selective admission processes could explain the large increase in comorbidities following PDPM, we consider an external measure of patient conditions: diagnoses from the referring hospital. We obtain all primary and secondary diagnoses at the referring

Figure 4. Incidence of SLP-Related and NTA-Related Comorbidities



Notes: Blue denotes comorbidities as recorded at the skilled nursing facility while orange denotes comorbidities as recorded at the preceding inpatient hospital stay. Coefficients are estimated using Equation 2, but the outcome variable is an indicator equal to one if any diagnoses are SLP- related (Left Subgraph) or NTA-related (Right Subgraph). 95% confidence intervals for each coefficient are displayed.

hospital by linking the main dataset on skilled nursing stays to patient hospital records.[30] If the increase in highly compensating comorbidities at opportunistic systems arises from selective admission, we should observe an increased prevalence of similar magnitude of these comorbidities at the referring hospital. Alternatively, if the increase in qualifying conditions arises from upcoding patients, then there should not be a corresponding increase in these measures using hospital claim data.

We utilize the same difference-in-difference design as in Equation 2 but using the diagnoses at the referring hospital. Figures 3 and 4 plot estimated coefficients when qualifying diagnoses are measured using hospital diagnoses in orange. Unlike diagnoses recorded by the skilled nursing facility, there is no discernible increase in Acute Neurologic diagnoses, SLP-related, or NTA-related comorbidities reported at the hospital for patients admitted to opportunistic systems after the adoption of PDPM. The increase in billings for these conditions must thus come from abnormal patient diagnoses made by the opportunistic SNF

[30]Hospital records come from the Hospital Inpatient Limited Data Set. Individuals are linked through an anonymized patient ID. Medicare reimbursements for hospitals did not experience changes that financially incentivize or disincentivize coding Acute Neurologic conditions, SLP-related comorbidities, or NTA-related comorbidities during the sample period.

systems that are strangely not diagnosed at the referring hospital.

4.3 Coding Intensity Around Mergers

Changes in ownership are often accompanied by shifts in management strategy which increase profits and cut costs (Eliason et al., 2020). If higher coding intensity at opportunistic systems is due to management-driven upcoding, then utilization of highly compensating codes should increase at facilities acquired by opportunistic systems. Utilizing the CMS Change of Ownership (CHOW) data, we identify 2,318 facility acquisitions occurring from October 2019 to December 2022, of which 1,327 were by a recognized SNF system. 561 of these acquisitions were by opportunistic systems.[31] We compare how billing practices change at facilities acquired by opportunistic systems to facilities not acquired during the sample period using a staggered difference-in-differences design. Recognizing recent empirical concerns that have been raised about the robustness and reliability of staggered difference-in-difference designs (Baker et al., 2022; Roth et al., 2023), we use a stacked cohort design akin to Cengiz et al. (2019). We include facility × cohort fixed effects to control for time-invariant heterogeneity at the individual facility-level that could be correlated with coding intensity. To capture aggregate time-series variation in coding intensity as providers learn to increase billings over time, we include a quarter-year × cohort fixed effect.[32] Figure 5 plots coefficients from a dynamic difference-in-differences regression of the form:

$$CodingIntensity_{ijt} = \alpha + \sum_{t=1}^{T} \beta_t Period_t \times AcquiredOpportunistic_j + FixedEffects + \epsilon \quad (3)$$

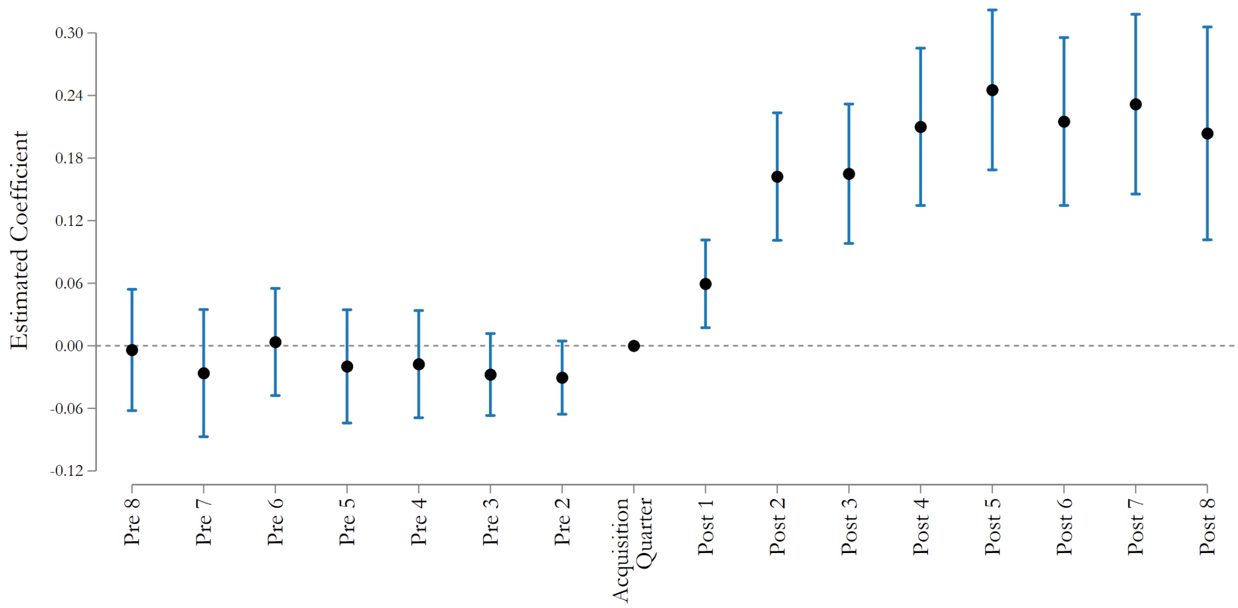
where $CodingIntensity_{ijt}$ is the sum of the five defined billing categories for patient i at facility j in quarter t. $Period_t$ is an indicator that denotes the quarter relative to acquisition.[33] Coding intensity increases sharply at facilities acquired by opportunistic SNF systems. Coding intensity increases in the first quarter following acquisition by 0.06 and continues increasing over the next four quarters before stabilizing at 0.245. Results are precisely estimated with coefficients on each treated quarter being significant at the 1% level.

[31] CMS identifies 9,682 of the 16,744 (58.9%) facilities as belonging to an SNF system. Due to complex ownership status as well as reliance on accurately reported ownership data, not all facilities belonging to a system may be identified.

[32] Acquisitions from SNF systems not classified as opportunistic systems are excluded so that the comparison is to facilities that do not experience any change in ownership over the sample period.

[33] Standard errors are clustered at the facility level. There do not seem to be differential pre-trends in the eight quarters prior to facility acquisition, suggesting that billing practices at acquired facilities do not fundamentally differ from billing practices from facilities that are not acquired.

Figure 5. Change in Coding Intensity around Acquisition



Notes: This figure plots estimated coefficients from Equation 3. Robust standard errors are clustered at the facility level. 95% confidence intervals for each coefficient are displayed.

Increases in coding intensity are driven by an increase in four of the five individual potential upcoding categories (Figure IA.6). The systematic and sudden increase in coding intensity at hundreds of facilities across the United States following acquisition is consistent with management-driven upcoding rather than patient selection explaining variation in billing.[34]

4.4 Quasi-Random Patient Assignment

Although patients admitted to opportunistic facilities appear similar along observable characteristics, unobservable patient conditions might be correlated with SNF choice. To instrument for facility selection, we use variation in occupancy constraints of local facilities. Occupancy constraints are relatively common in skilled nursing with 55% of facilities claiming they sometimes need to turn away prospective patients.[35] Patients tend to visit a nursing home in close proximity to their residence, with a median distance of less than five miles (Gupta et al., 2023), and facility choice is further limited by the operational capacity of SNFs

[34] Higher coding intensity by acquired facilities could also reflect a dramatic shift in the type of admitted patients, but hospital claims fail to support differences in comorbidities immediately preceding skilled nursing stays (as shown in Figures 3 and 4.)

[35] https://www.mcknights.com/news/ahca-offers-wake-up-call-on-bed-and-facility-counts-446000-residents-may-be-displaced/

in the area. We utilize variation in occupancy levels of competing facilities within a Hospital Service Area as a plausibly exogenous source of facility selection. The thought experiment is that a patient is more likely to visit a given facility when competitors are close to maximum occupancy.[36] To guide our empirical specification, we first begin by examining the likelihood that a patient is admitted to a particular facility j as a function of occupancy at all facilities $j \neq k$ which are in the same Hospital Service Area. We utilize a flexible local polynomial specification which (presented in Figure IA.7) and find that competitor occupancy has strong effects on patient selection, but only when competing facilities are close to full capacity. Motivated by our finding, we first utilize a piecewise linear specification to fit a probability of facility selection. Specifically, we estimate a regression of the form:

$$\pi_{ijt} = \alpha + \beta_1 Occ_{j\neq k,t-1} + \beta_2 Constrained + \beta_3 Constrained \times Occ_{j\neq k,t-1} + \epsilon \tag{4}$$

where π_{ijt} is the probability that patient i visits facility j in month t. $Occ_{j\neq k,t-1}$ is the average level of occupancy at competing facilities in the same Hospital Service Area and $Constrained$ is an indicator variable equal to one if the average level of occupancy across competitors exceeds 93%.[37] To construct the instrument, $PredictedExcessRehab$, we then use the fitted probabilities from Equation 4 to predict a weighted-average excess rehab that a patient is predicted to face ex-ante by aggregating over the facilities operating in the HSA according to:

$$PredictedExcessRehab_{ijt} = \sum_{j=1}^{J} \pi_{ijt} \times ExcessRehab_j \tag{5}$$

The identification assumption is that patient outcomes are unrelated to the instrument, except through the influence on choice of facility. We argue that the occupancy of competing SNFs in a small geographic region is plausibly exogenous to the underlying conditions of an individual patient. Furthermore, we provide indirect evidence of the exogeneity of the instrument utilizing data from hospital diagnoses at the end of this subsection. To miti-

[36]Utilization of geographical preferences to instrument for facility selection has been used in settings such as hospitals (McClellan et al., 1994; Card et al., 2023), nursing homes (Grabowski et al., 2013) and dialysis care centers (Wang et al., 2017).

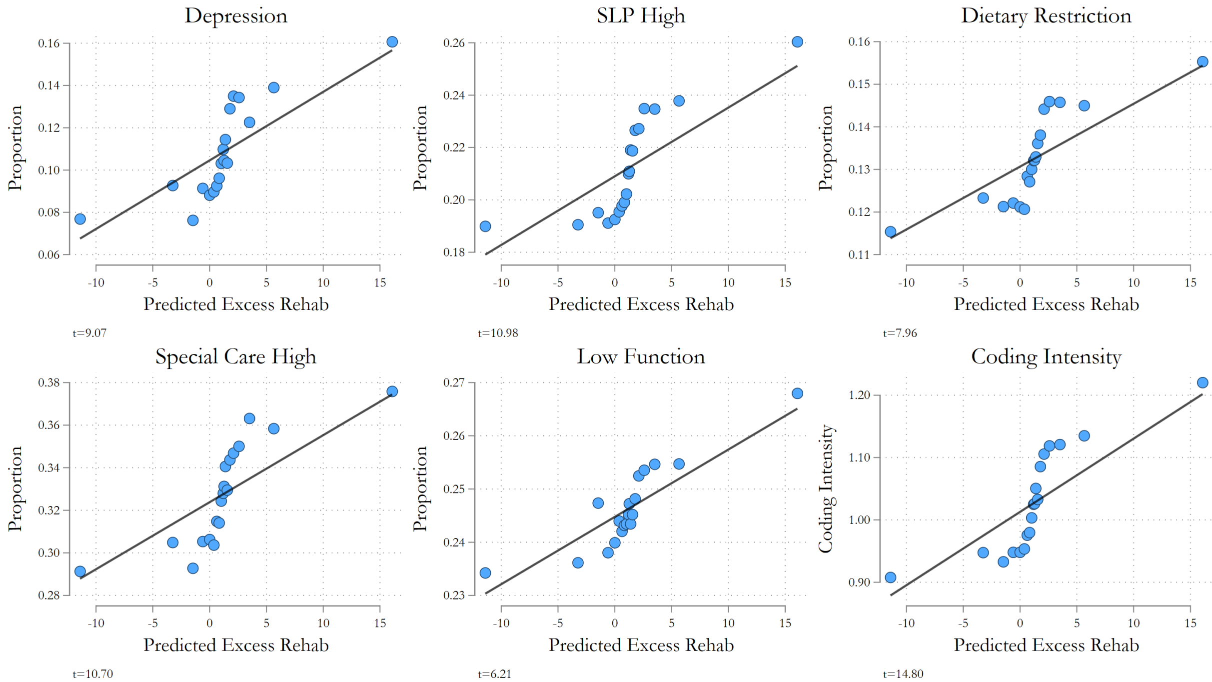
[37]This empirical threshold choice is guided by the empirical evidence in Figure IA.7, which indicates that occupancy constraints generally begin to bind around 93%. Nonetheless, we repeat the exercise using alternative cutoffs of 90% and 95% and find qualitatively similar results (as shown in Tables IA.XIII through IA.XVIII).

gate variation in excess rehab levels occurring over different geographic regions driven by geographic clustering of opportunistic systems, we include a HSA fixed effect in preferred specifications. This specification generates variation in predicted excess rehab due only to time-series variation in relative occupancy levels within a HSA.

To be a valid instrument, $PredictedExcessRehab$ also needs to be a strong predictor of the actual system opportunism a patient receives. We test the relevance condition by estimating a fage regression in Table IA.III. The constructed instrument strongly predicts the observed system excess rehab level (t statistic=10.78, F statistic=116.60).

We first visualize the reduced form relationship between the constructed instrument and each of our billing categories and total coding intensity in Figure 6. We then utilize the constructed instrument in a 2SLS framework to examine the relationship between excess rehab and PDPM coding intensity (presented in Table IA.IV). The coefficient of 0.026 implies that a shift from the first to third tercile of excess rehab (10.5 days) predicts increased coding intensity of 0.273, or about 27% of the unconditional mean. Estimated coefficients are similar to the 0.0244 estimated in OLS, suggesting that selective patient admission is not leading to large discrepancies in billing levels (Table 1). For the instrument to have a causal interpretation, the instrument must affect patient outcomes only through its impact on facility choice. This assumption might be threatened if there are time-varying and location-specific shocks that correlate with the distribution of facility occupancy and health outcomes. As an indirect test of the identification assumption, we examine the presence of patient comorbidities documented at the referring hospital. Consistent with competitor occupancy being plausibly exogenous to patient health outcomes, we find no evidence that the instrument is related to the presence of Acute Neurologic, NTA-related or SLP-related comorbidities immediately preceding the skilled nursing stay (as shown in Table IA.V).

Figure 6. Reduced Form Relation with Coding Intensity



Notes: This figure explores the relationship between billing practices in the RUG-IV era and coding intensity in the PDPM era by instrumenting for *ExcessRehab* using Equation 5. This figure plots a reduced form specification in which indicators for each individual billing category are regressed on *PredictedExcessRehab*. Each specification includes a HSA fixed effect and standard errors are clustered at the facility level.

4.5 Patients in SNFs During Transition

We then turn to the subset of patients who were in a skilled nursing facility during the regime change from the therapy-driven RUG-IV to comorbidity-driven PDPM. There is no reason to expect patient condition would sharply change around October 1, 2019, yet financial incentives for classifying patients change considerably. Since Ultra-High rehab patients were receiving a minimum of 12 hours per week of physical therapy, these patients need to have at least moderate physical function to complete the high levels of rehab.[38] It should thus be rare for such patients to be classified as either Low Function or Special Care High under PDPM, both conditions which indicate severe physical restrictions (as discussed further in Section 9.1). 42% of Ultra-High rehab patients at the most opportunistic systems

[38] CMS has stated that patients with the lowest levels of functional dependence, "likely reflects residents whose functional abilities are too impaired to receive intensive therapy." https://www.govinfo.gov/content/pkg/FR-2018-08-08/pdf/2018-16570.pdf

are billed as Low Function or Special Care High (as shown in Figure IA.8, Panel A).[39] In contrast, only 8% of patients at the facilities with the lowest levels of excess rehab. Regressions controlling for a rich set of patient fixed effects find similar results (as shown in Table IA.VI). This finding would be difficult to explain if opportunistic systems were accurately identifying patient needs. Either patients with limited physical function were receiving extreme amounts of therapy and/or patients who were in physical condition to endure frequent therapy were coded as having limited physical ability.

4.6 Within-Patient Switching Analysis

Finally, we consider patients who begin a second SNF stay within 14 days to compare coding practices across facilities for the same patient. For each patient, we compute the change in the frequency of PDPM coding intensity from the first facility.[40] High revenue categorizations for the same patient are more likely to be coded when a patient visits a system which previously had higher level of excess rehab. Differences in coding intensity are largest for the categories of Depression, SLP High, and Special Care High. Large differences in classification for high-revenue codes for patients admitted to different facilities within a short time period suggest that differences in observed coding intensity are related to system-level practices and are unlikely to be explained by unobservable patient heterogeneity.

4.7 Billing Practices and the Cost of Care?

Did the introduction of PDPM, which was intended to be budget-neutral, result in reduced reimbursements for systems that previously provided excess levels of rehab? [41] The cost of care increased considerably following the adoption of PDPM from $14,469 under RUG-IV to $16,148 under PDPM. Furthermore, the average cost of skilled nursing stay

[39] Low Function are cases in which a patient received the lowest category of physical function and patients are generally unable to complete mobility or self-care tasks on their own. Special Care High are patients receiving reduced physical function scores along with serious comorbidities such as septicemia, daily respiratory therapy, comatose, or fever with additional symptoms.

[40] For example, if a patient is classified as having depression at the second stay but not at the first, this is a change in depression of 1-0=1. We then compute this change in diagnoses for each of the billing categories when the patient visits a facility with lower prior excess rehab, when a patient visits a facility in the same system, or when a patient visits a facility with a higher level of excess rehab. Panel B of Figure IA.8 shows the change in PDPM coding intensity for each category when a patient visits a facility from a system with lower excess rehab (green), the same (blue), or higher excess rehab (red).

[41] Figure IA.9, Panel A plots the average cost per patient stay during RUG-IV (blue) and PDPM (orange) by decile of excess rehab. We compute the cost per stay as the total allowed amount which includes the sum that Medicare pays, deductible or coinsurance amounts that the beneficiary is responsible for, and any amount owed by a third party. SNF systems are sorted into deciles based on excess rehab as determined in Equation 1. We adjust for inflation to 2021 dollars.

varies considerably across SNF systems. Patients visiting a facility belonging to a system in the lowest decile of excess rehab has an average total cost of $14,323 compared to $20,002 for patients visiting facilities belonging to a system in the highest decile.[42] Overall, the findings indicate that the systems that were billing the most during the RUG-IV era are continuing to capture higher patient revenue under PDPM. For simplicity, we classify SNF systems in the highest tercile of excess rehab under RUG-IV as "opportunistic systems" going forward. We use billing practices during the RUG-IV period to classify systems so that it is prior to the main period of examination.

5 Do Opportunistic Systems Provide Superior Care?

SNF systems vary widely in revenue captured per patient, which could affect resources available for staffing, training, and investments in technology. If opportunistic systems use the additional Medicare revenue to pour into their patients, then patient outcomes and satisfaction should be higher at opportunistic systems. Alternatively, if billing differences reflect a culture focused mainly on profit extraction, then such facilities may also cut costs by lowering staffing and standards of care.

Examining quality of care is difficult because patient outcomes and characteristics are challenging for the econometrician to observe. We attempt to overcome this using three main approaches: first, we examine the prevalence of health outcomes such as pressure ulcers, urinary tract infections, rehospitalization, and mortality by augmenting SNF records with those from hospital and hospice visits immediately following SNF stays. Second, we examine perceived quality of care from detailed classifications of potential neglect and abuse using a large database of verified patient reviews. Third, we examine facility-level outcomes including staffing levels, health inspections, and inclusion on a CMS watchlist.

5.1 Patient Health Outcomes and Facility Practices

We first consider two health outcomes closely linked to poor care quality: Pressure ulcers, commonly known as bed sores, typically arise from extended periods of continuous pressure on skin, muscle, soft tissue or bones (Russo et al., 2008). UTIs, which often develop from poor hygiene practices such as use of bedpans rather than commodes, are one of the leading reasons for rehospitalization.[43] Recognizing the importance of UTIs and pressure

[42] The average cost to treat a patient who visited a facility in the lowest decile of excess rehab was $12,346 compared to $19,798 for patients who visited a facility in the top decile of excess rehab during RUG-IV.

[43] https://oig.hhs.gov/reports-and-publications/workplan/summary/wp-summary-0000733.asp

ulcers, CMS has included the development of these conditions in publicly reported quality measures. Yet, pressure to maintain high ratings may incentivize facilities to underreport such instances, so we utilize reports of these conditions at subsequent hospital stays. To focus on conditions that are likely to have developed at a SNF, we consider only patients in which a new hospitalization occurs within two days of SNF discharge and who did not already have a pressure ulcer or UTI when admitted to the SNF. This measurement is thus a lower bound as it only considers the 22.8% of SNF stays where patients are hospitalized within two days of discharge.[44] Finally, as measure of severe adverse conditions, we consider whether a patient is rehospitalized within 30 days or dies within 90 days.

After controlling for patient diagnoses and characteristics, system excess rehab is strongly and economically associated with greater pressure ulcers, UTIs, rehospitalization, and death (as shown in Table 2, Panel A). The coefficient for rehospitalization is 0.00239, which implies that moving from the first to the third tercile of system excess rehab is associated with an increased probability of rehospitalization of 2.51%,[45] which is an increase of 7.60% relative to the unconditional mean (of 33%). The same increase in excess rehab is associated with an increase in mortality of 1.62%, which is 9.63% of the unconditional mean.

[44] This extends the methodology from Integra Med Analytics (https://www.nursinghomereporting.com/ratings-methodology, https://www.nytimes.com/2021/03/13/business/nursing-homes-ratings-medicare-covid.html) which showed that SNF self-reported measures for pressure ulcers, UTIs, and falls are uncorrelated with the measures from matching hospital data as utilized by the NYTimes. To capture conditions that are likely to have occurred while at the skilled nursing facility, we exclude cases in which a patient was identified as having a UTI or pressure ulcer at the previous inpatient hospital stay. We also exclude minor diagnoses such as Stage 1 pressure ulcers, which might easily go unnoticed by staff. Additional details about how the lower bounds are constructed can be found in Appendix 10.

[45] A change from the first to third tercile of system excess rehab corresponds to an increase of 10.5 days of excess rehab, so the total effect on rehospitalization is 10.5 days $\times$ 0.00239 = 2.51%

Table 2. Excess Rehab and Patient Health Outcomes

Notes: This table presents OLS and IV results for regressions of patient health outcomes on SNF system excess rehab. Panel A presents results for OLS while Panel B presents two-state least squares results in which $ExcessRehab$ is instrumented using $PredictedExcessRehab$ as defined in Table IA.III. Fixed effects are as indicated at the bottom of each column. Robust standard errors are clustered at the SNF system level.

Panel A. OLS Results

	(1) Pressure Ulcer	(2) UTI	(3) Rehospitalized	(4) Mortality
Excess Rehab	0.000212***	0.000557***	0.00239***	0.00154***
	(7.91)	(12.39)	(11.75)	(9.59)
Patient Gender	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Length	Yes	Yes	Yes	Yes
Observations	6,194,050	6,194,050	6,194,050	6,194,050
Adjusted R^2	0.010	0.010	0.054	0.077

Panel B. IV Results

	(1) Pressure Ulcer	(2) UTI	(3) Rehospitalized	(4) Mortality
Excess Rehab	0.000200***	0.000545***	0.00259***	0.00227***
	(3.35)	(7.34)	(7.03)	(7.80)
Patient Gender	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Length	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes
Kleibergen-Paap F Statistic	111.8	111.8	111.8	111.8
Observations	1,609,904	1,609,904	1,609,904	1,609,904

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Endogenous matching between patients and facilities could lead to bias in the OLS estimates, so we instrument for system excess rehab by utilizing occupancy constraints of competing facilities within a Hospital Service Area as a source of quasi-random patient admission as discussed in Section 4.4. Compared to OLS estimates, IV estimates are similar in magnitude for pressure ulcers, UTIs, and rehospitalization, but we find about 50% larger effects for mortality (as shown in Table 2, Panel B). Instrumental variable specifications result in coefficients of 0.00259 and 0.00227 for rehospitalization and death, respectively which implies that a shift from the first to the third tercile of excess rehab causes increased hospitalization of 2.73% and increased death of 2.38%. Considering the 1.31 million patients visiting opportunistic systems from October 2019 to December 2022, this suggests an increase of 35,000 (1.31M × 2.73%) rehospitalizations and 30,000 (1.31M × 2.38%) deaths. Estimated coefficients of 0.00020 and 0.00055 for pressure ulcers and UTIs suggest that there are an additional 10,200 preventable health conditions ([0.00020+0.00055] × 10.5 days × 1.31M). We find robust evidence that patients at opportunistic SNF systems experience greater adverse health outcomes.

5.2 Patient Reviews

Patient reviews capture aspects of care provision that would be difficult to measure during ordinary annual health inspections. Two measures of patient satisfaction are considered first: review stars, which is the number of stars a patient left from one (worst) to five (best), and text sentiment, which is the overall sentiment of the review text and ranges from negative one to positive one.[46] We find that review stars and sentiment are lower at opportunistic systems. Results are economically and statistically significant—opportunistic systems receive reviews with 0.5 fewer stars.

5.2.1 Reviews Indicating Abuse

The overall star rating or sentiment could miss important nuance that is useful in capturing the quality of care. For example, consider these two reviews:

> This place is horrible. Don't leave your loved ones here. Nurse call button not answered for several hours. My Dad had a broken hip wasn't able to use the bathroom alone. It took several times to get a nurse and that was me asking for help. He had numerous bed sores and was never moved for several days. When we questioned the nurse she said "I am the only one here for over 30 patients.

> Absolutely terrible place... My grandpa could not even walk after going here. Was left soiled overnight and got horrible bed sores. Call button was left out of reach. Wasn't given water. But refusing to test him after seeing he was obviously sick is pure neglect to him and other patients. Nasty place.

Such descriptive reviews can provide insight into patient care quality. A supervised learning approach is used to quantify patient abuse. The process begins with a manual classification of 100 reviews indicating abuse, such as the reviews above, and 100 that do not. We then use a Support Vector Machine (SVM) algorithm to identify and classify reviews.[47]

[46] We estimate a regression of these measures of patient satisfaction on system excess rehab and present a binscatter in Figure IA.10.

[47] Specifically, we use the Linear Support Vector Classifier from the sklearn library with default parameters.

The algorithm gives a predicted probability that a given review is indicative of abuse. Abuse appears to be a pervasive feature of SNF reviews: 16.7% of reviews are classified as indicating abuse with probability exceeding 90%.[48] We examine whether abusive reviews are related to opportunistic system billing practices by estimating a regression of the form:

$$Abuse_{rj} = \alpha + \beta SystemExcessRehab_j + \epsilon$$

where $Abuse_{rj}$ is a measure of whether review r at a facility belonging to system j indicates abuse and is an indicator variable equal to one if the fitted probability of abuse exceeds 90%. We visualize the relationship from this regression in Figure 7 by plotting a binscatter of abusive reviews against system excess rehab. The most opportunistic systems in the top decile of excess rehab have over 19.1% of their reviews categorized as abusive as compared to 7.1% in the bottom decile. Overall, there is a strong relationship between the level of excess rehab and abusive reviews (t statistic=7.07). Although online reviews indicate lower sentiment, review stars, and greater abuse for systems with greater excess rehab when aggregated to the system-level, prospective patients may have difficulty using reviews to screen individual facilities because individual reviews are noisy and the average individual facility contains only four reviews. Furthermore, many prospective patients may be unaware of the presence of the online reviews when making care decisions.

5.3 Staffing

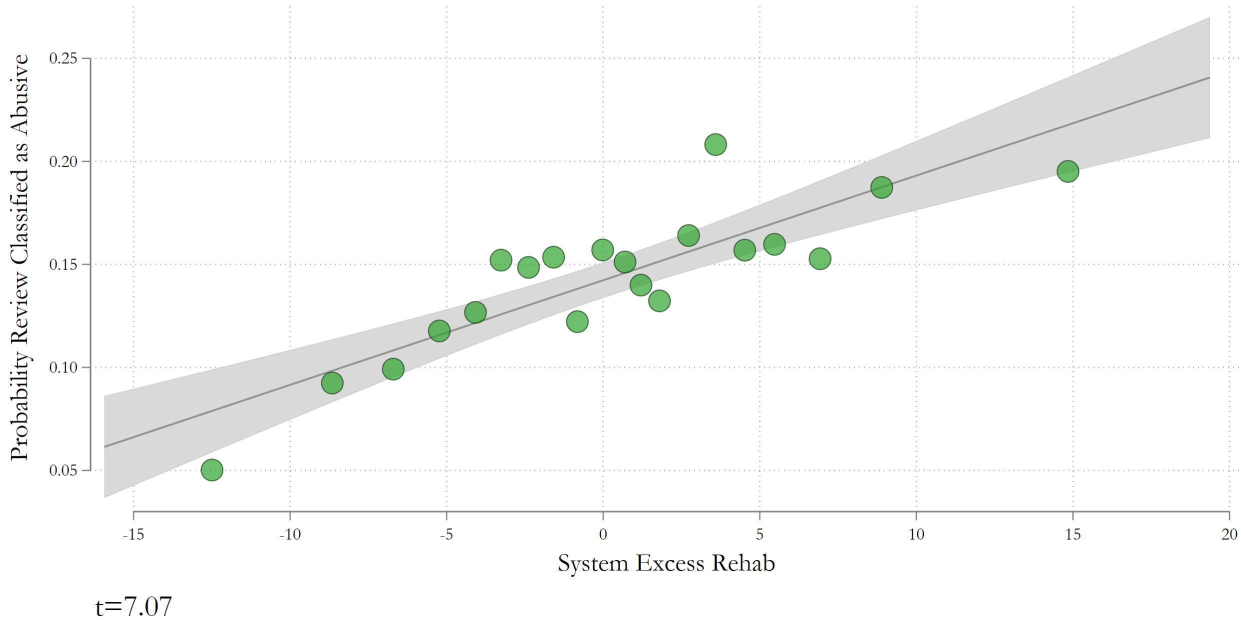
Skilled nursing facilities need sufficient nurse staffing to effectively treat patients (Tong, 2011; Friedrich and Hackmann, 2021). Yet, there has been increased concern that staffing levels could be inadequate, and some states such as New York have recently passed legislation requiring minimum nursing hours.[49] Are SNF system billing practices related to nurse staffing decisions? We estimate a regression of nursing staff hours on a system's excess rehab in Table 3.[50] Systems with higher levels of excess rehab provide 0.5 fewer nursing hours per resident day, mostly driven by reduced staffing for Nursing Aids and Registered Nurses. Dif-

[48] Patients experiencing abuse may be disproportionately more likely to leave a review so this may not reflect aggregate incidence of abuse in nursing homes. However, our focus is on the relative frequency of abuse across different systems.

[49] https://www.health.ny.gov/facilities/nursing/minimum_staffing/

[50] We present a binscatter of this regression in Figure IA.11. Because minimum nursing requirements may differ by state, we include county and state × year fixed effects in these facility-level regressions (as shown in Table 3).

Figure 7. Excess Rehab and Abusive Reviews



Notes: This figure fits a binscatter between the likelihood of a patient review being classified as abusive and a system's excess rehab. Abusive reviews are those identified with greater than 90% confidence by the SVM algorithm.

ferences in staffing levels across facilities by type are economically important with patients at facilities with the lowest excess rehab receiving 47.4 minutes of care provided by a Registered Nurse per resident day compared to only 30 minutes per day at the most opportunistic facilities.

5.4 Outcomes from Unannounced State Inspections

To participate in Medicare, facilities must undergo periodic on-site health inspections from state agencies approximately once per year. Inspections are supposed to be unannounced and not anticipated by facilities. CMS assigns facilities a rating from one (worst) to five (best) stars based on the number, scope, and severity of deficiencies over the previous three years. We examine whether a system's excess rehab is related to health inspection ratings, weighted health deficiencies, the number of substantiated complaints, or the total amount of assessed fines.[51] estimating a regression of each quality of care variable on a

[51] Complaints that are not validated through health inspection or issuance of a citation are not included in the CMS data set, so this is a substantial lower bound.

Table 3. Excess Rehab and Nurse Staffing Levels

This table presents coefficients from the following OLS regression:

$$y_{jt} = \alpha + \beta ExcessRehab_j + FixedEffects + \epsilon_{jt}$$

where y_{jt} ie either a measure of staffing hours per resident day. Finally, the outcome variable in column 5 is the staffing rating released by CMS which ranges from one (worst) to five (best). Fixed effects are as indicated at the bottom of each column. Robust standard errors are clustered at the SNF system level.

	(1) Nurs. Aid	(2) LPN	(3) RN	(4) Total	(5) Staff Rating
Excess Rehab	-0.0116***	-0.00136	-0.0149***	-0.0286***	-0.0422***
	(-6.43)	(-1.43)	(-8.09)	(-8.17)	(-8.53)
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	53,188	53,188	53,188	53,188	53,181
Adjusted R^2	0.383	0.404	0.437	0.348	0.404

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

SNF's system excess rehab.[52] SNF systems with greater excess rehab perform more poorly on unannounced health inspections, have more substantiated resident complaints, and receive greater total fines from CMS. The most opportunistic facilities experience more than twice as many substantiated complaints, 40% more fines, and 60% higher deficiency scores (as shown in Figure IA.12).

6 Do Opportunistic Systems Experience External Regulatory, Reputational, or Patient Discipline?

What are the incentives and disciplining mechanisms systems face for upcoding? Systems that engaged in excess rehab boosted revenues while providing lower quality of care through cost-cutting measures such as reduced staffing. Opportunistic behavior might be mitigated if systems are punished through regulatory or reputational channels. Regulator intervention could discipline systems through payment denials, fines, blocking of mergers, or information disclosure.

[52]Figure IA.12 presents binscatters of these regressions.

6.1 Do Opportunistic Systems Game CMS Ratings?

CMS collects and distributes information about patient health outcomes called "Quality Measures" to "assure quality health care for Medicare Beneficiaries through accountability and public disclosure".[53] Quality Measures are publicly and prominently featured in the CMS "Five-Star" ratings, which is the predominant source of data available to most patients and their guardians. Quality Measures depend on accurate reporting from SNFs to CMS, but facilities may face incentives to underreport incidents that would reduce ratings. We investigate whether opportunistic systems are more or less likely to underreport negative health outcomes. There is a strong relationship between system type and the underreporting of pressure ulcers. 41% of facility-quarters for systems in the top decile are underreported compared to 22% of facility-quarters for systems in the lowest decile.

Utilizing patients who begin a new hospital stay within two days of leaving a SNF, we construct a lower bound for adverse health outcomes developed at the SNF (as discussed in Sections 5.1 and 10). Comparing our conservative lower bound of pressure ulcer development, we find that underreporting is a pervasive feature for Quality Measures. The average publicly reported quality metric of pressure ulcer development during this time period is 0.77%, yet we find an average lower bound that is 65% higher at 1.28%. The lower bound of new pressure ulcers exceeds reported quality metrics for 38.2% of facility-quarters and is more than double for 31.9% of facility-quarters.

Is underreporting of pressure ulcers related to a system's past excess rehab? We estimate a regression of pressure ulcer underreporting on system excess rehab and find that systems with higher excess rehab are far more likely to underreport (as shown in Figure IA.13, Panel B).[54]

To validate the lower bound of pressure ulcer development we use the sample of nursing home reviews. We find that reviews mentioning pressure ulcers are positively and strongly

[53] https://www.cms.gov/medicare/quality/measures

[54] To be conservative, we consider facility-quarters to be underreported only if the estimated lower bound is at least twice the reported quality metric. Systems with high excess rehab underreport pressure ulcers by at least 100% in 41.5% of facility-quarters, whereas for systems with low levels of excess rehab, the same level of underreporting of pressure ulcers only occurs in 21.7% of quarters and the relationship is estimated precisely (t=9.52).

associated with the constructed lower bound, but are uncorrelated with official CMS quality metrics (as shown in Figure IA.14). These results provide external validity that the lower bound constructed from hospital claims is a reasonable approximation of pressure ulcer incidence for SNF patients and that CMS quality metrics may not be reliable due to SNF underreporting. In addition to pressure ulcers, we also find that facilities with higher excess rehab are more likely to potentially underreport traumatic falls and UTIs, though our data covers a different subset of patients.[55]

6.2 Payment Denials and Special Focus Facility

Does Medicare deny more claims from opportunistic systems? Claims can be denied for reasons such as care not meeting medical necessity or exceeding frequency limitations. We find opportunistic SNF systems are more likely to have claims denied for payment. However differences in rejection rates are economically small.[56]

Finally, we examine whether opportunistic systems are more likely to be named by CMS as a Special Focus Facility, a designation indicating systemic issues.[57] SNF systems with greater excess rehab are more likely to be included as a special focus facility (Table IA.VII). Increasing from the first to third tercile of excess rehab is associated with increased probability SFF designation of 0.61%, which is quite large relative to the unconditional average of 0.54%. Nonetheless, typically fewer than 100 facilities are identified as problematic, hindering such status as being a useful signal of quality for most patients.

6.3 Patient Retention

Due to misleading public ratings as well as difficulty accessing or analyzing data, patients may have a challenging time ascertaining facility quality when assessing options. We investigate whether patient retention is related to system excess rehab utilizing patients with

[55] These results are shown in Figure IA.15, Panels B and D). CMS Quality Metrics are reported for Long-Stay Patients who have been in the facility for more than 100 days, but our data covers only short-stay patients with a length of stay of less than 100 days. Thus, unlike with pressure ulcers, we do not measure the same subset of patients as in the CMS Medicare quality metric. We also find that our lower bound measure of UTIs is positively associated with online reviews mentioning UTIs (as shown in Figure IA.16). For traumatic falls the results are statistically insignificant consistent with the very low frequency of traumatic falls.

[56] The coefficient of 0.0044 implies that a shift from the first to third tercile of system excess rehab would increase the number of expected payment denials by only 0.046 (0.0044×10.5) per year (Table IA.VII).

[57] The Special Focus Facility program was introduced to identify skilled nursing facilities with "underlying systemic problems that give rise to repeated cycles of serious deficiencies, which pose risks to residents' health and safety." https://www.cms.gov/medicare/provider-enrollment-and-certification/certificationandcomplianc/downloads/sfflist.pdf

multiple SNF stays during the sample period. Retention rates are relatively large between 56% and 61%, meaning that most patients with multiple stays utilize the same facility. Consistent with patients themselves having a difficult time ascertaining quality, we find that system opportunism is not related to patient retention (as shown in Figure IA.17).

7 Spread of Billing Practices

Does opportunistic billing practices affect firm expansion? Excess profit extraction through aggressive billing and cost-cutting measures, such as reduced staffing, could fund acquisitions and expansions. However, firm reputation or regulator intervention might mitigate such behavior in the long run. Merger activity for facilities with excessive billing practices might also be limited if state regulators are more likely to deny licensure to entities with poor historical performance.[58]

7.1 Are Opportunistic Systems Involved in Fewer Acquisitions?

Do SNF systems with aggressive billing practices expand more or less quickly? Utilizing the CMS Change of Ownership (CHOW) database, we find that opportunistic systems acquired 1,091 facilities, more than twice the number of facilities acquired by systems in the lowest tercile of excess rehab (483) as shown in Figure 8. Greater expansion of systems that engage in aggressive billing practices suggests upcoding may increase profitability and fuel growth. Expansion also implies increased costs and reduced quality going forward.[59]

7.2 Ownership Structure and Facility Billing Practices

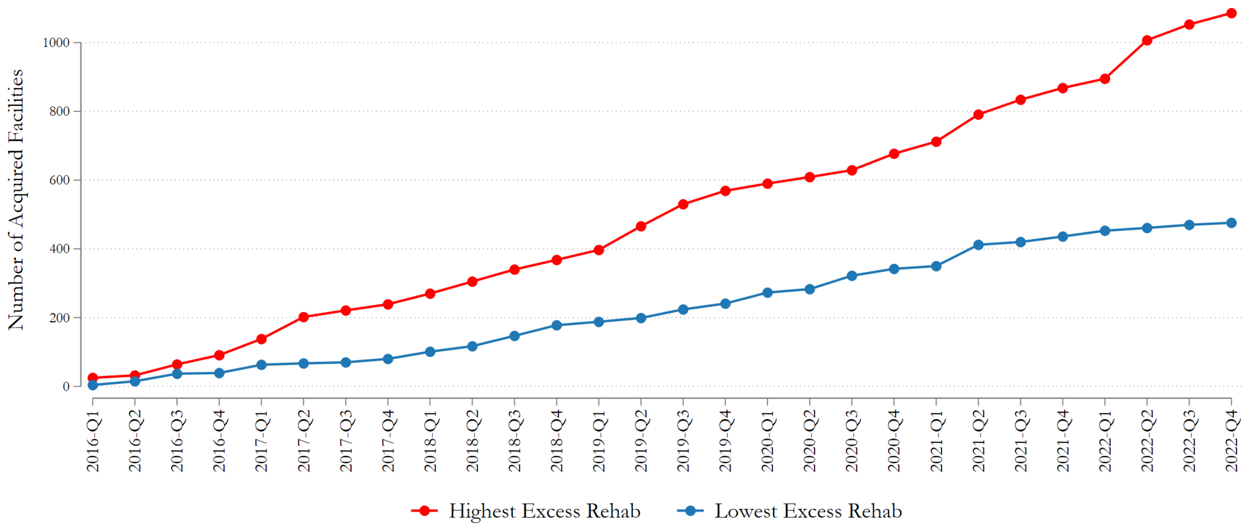
Are excess billing practices related to facility ownership structure? Broad ownership types of SNFs are for-profit, non-profit, and governmental. Skilled nursing is dominated by for-profit facilities with 74.2% of patients.[60] Non-profit (governmental) facilities account for the remaining 22.4% (3.4%). To investigate the relations between ownership type and billing

[58]CMS suggests that state regulators may use aggregate performance of affiliated entities when screening acquisitions.https://data.cms.gov/sites/default/files/2023-06/FAQ_Affiliated_Entity_Performance.pdf

[59]The majority of acquisitions do not appear to be private equity. According to data that we can collect, we only find that 8.74% of acquisitions during the sample period and 5.78% of acquisitions among facilities acquired by opportunistic systems are from systems with private equity backing. However, since it is difficult to determine full private equity ownership and our datasets may be incomplete, private equity ownership may be slightly greater than measured. Additional analysis is presented in the Internet Appendix 10.2.

[60]Private-equity-backed systems account for a relatively small portion of facilities at 6.4% in the data we collect. We cannot ensure that every PE-backed facility is identified due to data quality issues as well as incomplete data. The 6.4% of facilities we identify is slightly lower than the approximately 8% of facilities identified by Gupta et al. (2023) in 2017.

Figure 8. Spread of SNF Systems by Excess Rehab



Notes: This figure plots the cumulative number of acquisitions since January 2016. SNF systems which were in the highest tercile of excess rehab are plotted in red while SNF systems in the lowest tercile are plotted in blue.

practices, we sort facilities into deciles based on either system excess rehab or PDPM coding intensity and examine the relative types of ownership within each decile (in Figure IA.18). Non-profits make up a much larger proportion of systems with low excess rehab. In the bottom decile (half) of excess rehab, non-profits are responsible for 44.2% (22.2%) compared to only 2.6% (3.6%) of systems in the highest decile (half). During PDPM, 38.8% of the lowest coding intensity systems are non-profit whereas the top decile only has 3.6% non-profit. Although excess billing is generally higher at for-profit systems, it is worth noting that for-profits are still the dominant ownership type in below-average billing facilities, indicating that many privately-owned SNFs are sustainable with lower billing levels.

Is SNF system size related to billing practices? The majority of analysis focuses on SNF systems identified by CMS affiliation, which requires a minimum of at least two facilities. We compare billing practices for standalone facilities, small systems with ten or fewer facilities, medium systems with 11-25 facilities and large systems with more than 25 facilities. Non-profit facilities are more likely to be operated independently with 63% of non-profit facilities operating on a standalone basis compared to only 25% of for-profit facilities. Recognizing the relationship between a facility's billing and for-profit status, we examine whether system size is related to either excess rehab or coding intensity separately for non-profit and for-profit facilities (in Figure IA.19). Among for-profit facilities, we find that independent facilities do not bill at meaningfully different levels than larger SNF systems.[61]

7.3 Discussion of Upcoding Costs

We consider the potential costs arising from patient upcoding at facilities in opportunistic systems The average cost per patient for a facility in the top (bottom) tercile of excess rehab is \$18,125 (\$14,827). Given the approximately 404,000 patients visiting facilities in opportunistic systems each year, this suggests increased costs of treatment of more than \$1.33 billion per year,[62] approximately 5% of total SNF Medicare spending. We also acknowledge that upcoding can occur at systems not in the top tercile of excess rehab and hence these estimates may undercount total costs. Furthermore, we estimate that \$526.78, or 16%, of the additional cost per resident stay arises from specific upcoding in the Nursing and SLP components alone.[63] Considering the growth of opportunistic systems documented in Section 7.1, long-term costs are likely to increase as opportunistic systems capture additional market share.

8 Conclusion

Competition typically leads to better prices, products, and quality, but with fixed Medicare prices SNF providers should compete on quality of service. If patients select facilities with better service and health outcomes, SNF systems would need to compete on providing high quality health care. However, if patients have local preferences and experience difficulty evaluating providers due to noisy ratings and lack of data on health outcomes, providers may focus on extracting rents by maximizing billings and providing minimal care. Our findings indicate that such a setting seems to be present for many SNF systems which simultaneously and consistently defraud Medicare while simultaneously providing subpar care.

Our findings suggest many areas for potential reform and further investigation. First,

[61] There is some evidence that larger non-profit systems had slightly greater excess rehab during RUG-IV, but we caveat this result is driven by a small number of non-profit systems.

[62] 404,000 $\times$ (\$18,125-\$14,827)=\$1.33 billion.

[63] We compute the excess revenue generated from the SLP component as the actual SLP revenue collected from facilities in the top tercile minus the amount of revenue that would have been collected if the SLP case-mix was the weighted average case-mix of facilities outside the top tercile of excess rehab assuming the same number of days. Details are provided in the Internet Appendix.

the fact that SNF systems have such widespread and persistent differences in fraud and health outcomes indicates that better care at lower prices is feasible by many systems. Enforcement and policy should focus more on system-wide practices due to greater precision and more powerful tests. Second, given that existing methods of reporting preventable health outcomes are gamed, much more attention needs to be spent on measuring and quantifying patient health outcomes. Academic research can assist by providing more transparency and monitoring, which would be more efficient if CMS made additional granular data available. Third, enforcement penalties need to be substantially increased. Given the adverse health outcomes and corporate limited liability, more criminal charges (Coffee Jr, 1980; Polinsky and Shavell, 1993) may be needed to increase penalties in a setting where management is complicit. Fourth, since SNFs frequently tunnel funds through excessive management and rental rates to shield against lawsuits (Gandhi and Olenski, 2024), SNFs that take funds from Medicare should be prohibited from using shell companies to syphon funds. Fifth, other effective monitoring tools such as Medicare's Recovery Audit Contractor (RAC) Program (Shi, 2023) and DOJ settlements (Howard and McCarthy, 2021) which have both been shown to have strong deterrent effects should be used more aggressively. Sixth, SNF mergers and acquisitions should only be approved for systems that are both providing quality care to patients and within the norms of appropriate billing. Finally, more accurate and detailed data needs to be compiled and available to patients and their guardians so that they can make more informed decisions when selecting facilities.

Although not all these reforms may be necessary, given imperfect information, legal and regulatory hurdles, administration inefficiencies, and likely substantial legal and political capital spent by fraudulent SNFs to thwart these outcomes, radical reforms appear warranted to disincentivize bad actors and reward the many SNF systems that are providing better care at lower costs.

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Supplemental Internet Appendix

9 PDPM Reimbursement Components

9.1 Nursing Component

The Nursing component of PDPM is determined by a patient's underlying diagnosis, intensity of services needed, physical function score, and depression status. Within broad hierarchical categories reflecting the extensiveness of required services, patients are assessed for depression. A final case-mix is assigned using a patient's level of physical function as shown in Exhibit 1. Patients with more intensive nursing needs, depression, or lower levels of physical function are eligible for higher daily reimbursements for the Nursing component. Daily reimbursements for the Nursing component (in 2022) range widely from \$68.28 to \$420.05.

When considering coding intensity, we first measure whether a patient is classified in the treatment category of Special Care High. To qualify for this level of care, a patient must have a Function Score of 14 or less and suffer from a specified serious medical condition (such as septicemia, daily respiratory therapy, comatose, or fever with additional symptoms). Patients classified into one of the Special Care High case-mixes are shown in Exhibit 1 by the pink boxes and arrows. The Special Care High case-mix groups have among the highest daily reimbursement amounts.[64]

Patients are then screened by skilled nursing staff for signs of depression using the Resident Mood Interview or Staff Assessment of Resident Mood. Nursing case-mixes with a depression diagnosis are denoted by the brown boxes and arrows on Exhibit 1. The final step in determining reimbursement for the Nursing component is classifying patients into distinct categories based on the level of physical function. Patients are scored on a scale of zero to 16 based on their ability to complete tasks involving mobility and self-care such as ability to get in and out of bed, sit/stand, and oral/toilet hygiene with a higher score indicating that a patient can complete more tasks independently. Patients who can complete fewer tasks on their own are eligible for higher daily reimbursements. For expositional purposes, we refer to case-mixes with a Nursing Function Score of five or below the lowest category, as "Low Function" (denoted by the turquoise boxes and arrows in Exhibit 1). Patients classified

[64] Extensive Services case-mix groups have higher daily reimbursements, but have extremely strict requirements to classify such as having an active Tracheostomy or Ventilator and are easier to verify.

as Low Function need substantial support in every category of assessment and are unable to complete basic self-care and mobility tasks on their own. Differences in reimbursement can be substantial—a patient qualifying for Special Care High with depression and low mobility would qualify for daily reimbursement of $248.30 whereas a patient without such condition would qualify for a maximum daily reimbursement of $147.95.

9.2 SLP Component

The Speech Language Pathology (SLP) component of reimbursement features 12 possible case-mix indices with daily reimbursement rates ranging from $15.06 to $93.25 per day as demonstrated in Exhibit 2. Patients are first screened for having an Acute Neurologic primary diagnosis, additional SLP-related comorbidities, and cognitive impairment. SLP reimbursement is increasing in the count of such conditions. SLP-related comorbidities are conditions that increase the cost of SLP-related care and include traumatic brain injuries, oral cancers, or speech and language deficits. Cognitive impairment is determined by staff and any level of cognitive impairment that is mild or above qualifies for higher reimbursement rates. For expositional purposes, we consider "SLP High" case-mixes as those in which a patient is billed for at least two of the three qualifying conditions and highlight such case-mix indices using yellow boxes and arrows in Exhibit 2.

Once patients have been sorted into an initial bucket, a SLP case-mix is assigned based on the presence or absence of dietary disorders. Patients qualify for a higher SLP reimbursement if they require a mechanically altered diet, have a swallowing disorder, or both. Swallowing disorders include symptoms such as coughing, choking, or experiencing pain while swallowing. We classify a patient as having a dietary restriction if they are billed as having both a mechanically altered diet and a swallowing disorder. Dietary Restriction case-mixes are illustrated in Exhibit 2 by the light blue boxes and arrows. Patients coded as having at least two of an Acute Neurologic primary diagnosis, SLP-related comorbidities or cognitive impairment along with a dietary restriction would qualify for a daily SLP reimbursement of at least $78.19 compared to a maximum reimbursement of $32.34 without such conditions.

10 Construction of Lower Bounds of Health Outcomes

The lower bound of condition incidence is computed using Medicare claims for future hospital stays that occur within two days of a patient leaving a SNF. Specifically, the lower bound is defined as:

$$LowerBound = \frac{\text{\# Patients Admitted to Hospital within 2 Days \& Acquired Condition}}{\text{\# of Patients Visiting Facility}}$$

For Urinary Tract Infections, we follow the methodology outlined by The Agency for Healthcare Research and Quality (AHRQ) and exclude cases in which the UTI may have been due to certain kidney diseases or immunodeficiencies. We allow the UTI to be any primary or secondary diagnosis.[65] Identifying falls and trauma is somewhat more challenging. We utilize a CMS report (Segal et al., 2014) which identifies patient diagnoses related to falls and trauma that could identify potentially avoidable conditions. We consider only cases in which the first or second diagnosis.

10.1 Additional Compensation from Upcoding in Nursing and SLP Components

Because the Nursing and SLP components of PDPM reimbursement are the most subject to manipulation, we focus on these categories and explore how much additional revenue would be generated from upcoding at dubious facilities. SLP case-mixes have a case-mix index (reimbursement multiplier) ranging from 0.68 to 4.19 implying daily SLP reimbursement can range from \$15.95 to \$98.26.[66] We first compute the distribution of case-mixes for patients visiting facilities outside of the top tercile of excess rehab and compare this with the distribution of case-mix for opportunistic systems.[67] Facilities in the opportunistic systems have a weighted average SLP case-mix index of 1.95 versus 1.73 for others.

We compute the excess revenue generated from the SLP component as the actual SLP revenue collected from facilities in the top tercile minus the amount of revenue that would have been collected with an industry-average case-mix assuming the number of days is held constant.[68] Performing this adjustment, we find that facilities in opportunistic systems generate an additional \$213 Million in SLP revenue from October 1, 2019 to December 31, 2022.

[65] https://qualityindicators.ahrq.gov/Downloads/Modules/PQI/V2019/TechSpecs/PQI_12_Urinary_Tract_Infection_Admission_Rate.pdf

[66] This range is computed by taking the range of case-mix indices and multiplying by the daily base rate for SLP of \$23.45.

[67] For example, opportunistic systems bill more days (3.43%) at the highest level of reimbursement for SLP than other facilities (2.08%).

[68] Intuitively, this assumes that the distribution of case-mixes that is billed by other facilities is representative of the underlying population.

Nursing case-mix indices range from 0.66 to 4.04 so per diem reimbursement for nursing can range from $72.28 to $442.42. As before, we compute the potential excess revenue generated from facilities in opportunistic systems as the amount of Medicare billings minus the counterfactual billings that would arise with a distribution of case-mix observed in the other group. Facilities in opportunistic systems generated an additional $476 Million in Nursing revenue during PDPM. From Nursing and SLP we find a total of $689 Million in additional revenue which is generated by coding more aggressive case-mixes.

10.2 Private Equity and Skilled Nursing

Private equity has been linked to reduced SNF staffing and mortality (Gupta et al., 2023) and fewer resources for COVID-19 (Braun et al., 2020). The Federal Trade Commission (FTC), Department of Justice (DOJ) and the Department of Health and Human Services (HHS) have announced new inquiries into the role of private equity in healthcare.[69]

Although CMS has recently published data on the ownership of skilled nursing facilities as well as mergers and acquisitions occurring since 2016, which is a substantial improvement in transparency, identifying private-equity presence in skilled nursing facilities remains difficult. The Government Accountability Office (GAO) as well as academics and private journalists have found that private equity owners often obfuscate ownership by either not reporting ownership to CMS as required, or by utilizing affiliated entities who could not easily be linked back to the final private equity investor (GAO, 2023; Chen et al., 2024).

We investigate the role of private equity by examining how practices vary across ownership types. By focusing on private-equity firms that have large skilled nursing facilities, we identify 788 facilities that are operated by a SNF system with at least partial PE-backing. While we cannot ensure that have matched every PE-backed nursing home due to data quality issues (Gupta et al., 2023), we note that PE-backed skilled nursing facilities represent a relatively small portion of all skilled nursing facilities. While 71.7% of skilled nursing facilities operate as for-profit entities, we find only 5.25% of facilities identified as having PE-backing.[70]

[69]https://www.goodwinlaw.com/en/insights/publications/2024/03/alerts-privateequity-hltc-ftc-and-doj-launch-new-cross-government-inquiryhttps://www.hhs.gov/about/news/2023/11/15/biden-harris-administration-continues-unprecedented-efforts-increase-transparency-nursing-home-ownership.html

[70]This figure is similar to the 5% that is identified in GAO (2023) and Braun et al. (2020), but lower than the approximately 8% of facilities identified by Gupta et al. (2023) in 2017. We utilize private equity investments identified by O'Grady (2021) and Lincoln (2022) and manually match this to the CMS ownership data. PE-backed investment is often obfuscated by omitting ownership information or by utilizing non-descript subsidiaries. We classify an SNF system as PE-backed if any of their facilities have listed ownership

Private equity owned facilities account for 6.8%, 14.3%, and 6.1% of systems in the bottom, middle, and top terciles of excess rehab, respectively. Coding intensity from PE-facilities is economically similar and not statistically different than other for-profit facilities, but is notably higher than non-profit facilities (as shown in Figure IA.IA.20). PE-owned systems have an average coding intensity of 0.95 which is similar to 0.92 for other for-profit systems, but lower than the 1.08 observed for opportunistic systems. There is considerable cross-sectional billing differences among PE-backed systems with coding intensity ranging from 0.69 to 1.18. Costs per patient are also similar with an average of $16,136 per patient for PE-backed facilities versus $16,710 per patient for non-PE for-profit facilities. We also find that while private equity systems are spreading faster than average, they still represent a relatively small portion of overall acquisitions at 8.74%. While not meant to be comprehensive of PE-backing, our brief examination indicates that other types of private ownership are most common among upcoding systems.

tied to private equity. Given that our sample if manually constructed, we may miss smaller PE-backed systems.

Exhibit 1. Nursing Case-Mix

This diagram demonstrates how patients are sorted into nursing case-mixes for the Nursing component of PDPM. Patients are first sorted into six buckets in a hierarchical order based on underlying patient conditions with earlier classifications qualifying for higher daily reimbursement. Patients are then sorted based on the presence of a tracheostomy or ventilator, depression, or intensity of nursing rehab. Finally, patients are sorted into a final case-mix using their functional score on section GG. Special Care High denotes patients that are classified into the Special Care High classification (pink bucket), Depression denotes that a patient was billed for depression (brown boxes), and finally Low Function means that a patient was billed for a functional score of five or below (turquoise boxes). Daily reimbursement for each case-mix is displayed in the further right column.

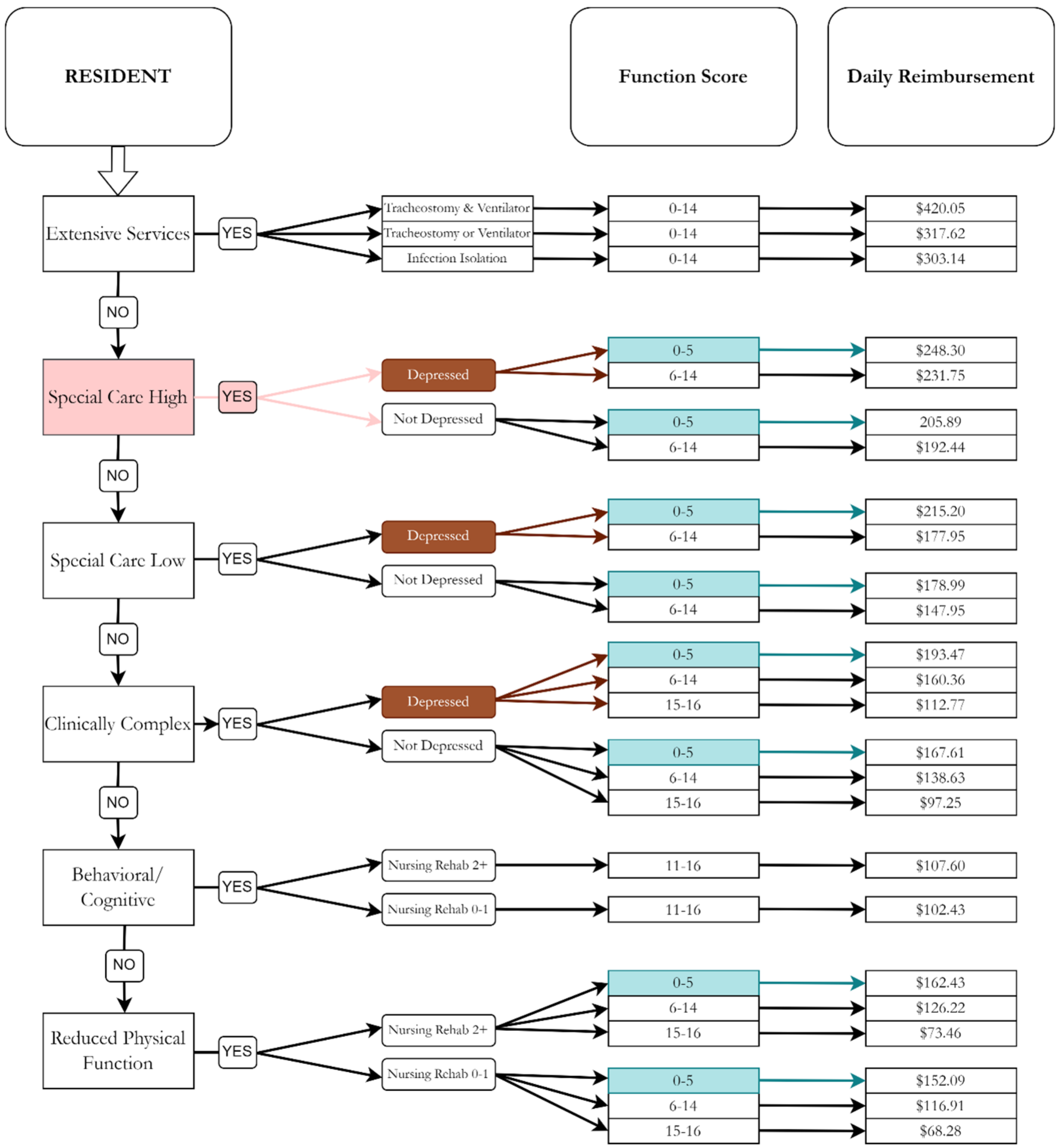


Exhibit 2. Speech Language Pathology (SLP) Case-Mix

This exhibit displays how patients are sorted into possible case-mixes for the Speech Language and Pathology component of PDPM care. Patients are first sorted by whether they have an Acute Neurologic primary diagnosis, an SLP-related comorbidity, or cognitive impairment. We classify a patient at SLP High if they have at least two of the conditions as denoted by the yellow boxes. Patients are then sorted based on dietary restrictions including whether a patient has a swallowing disorder or a mechanically altered diet. We classify a dietary restriction if a patient has both a swallowing disorder and a mechanically altered diet as denoted by the blue boxes. The right-most column displays how much reimbursement each case-mix is entitled to.

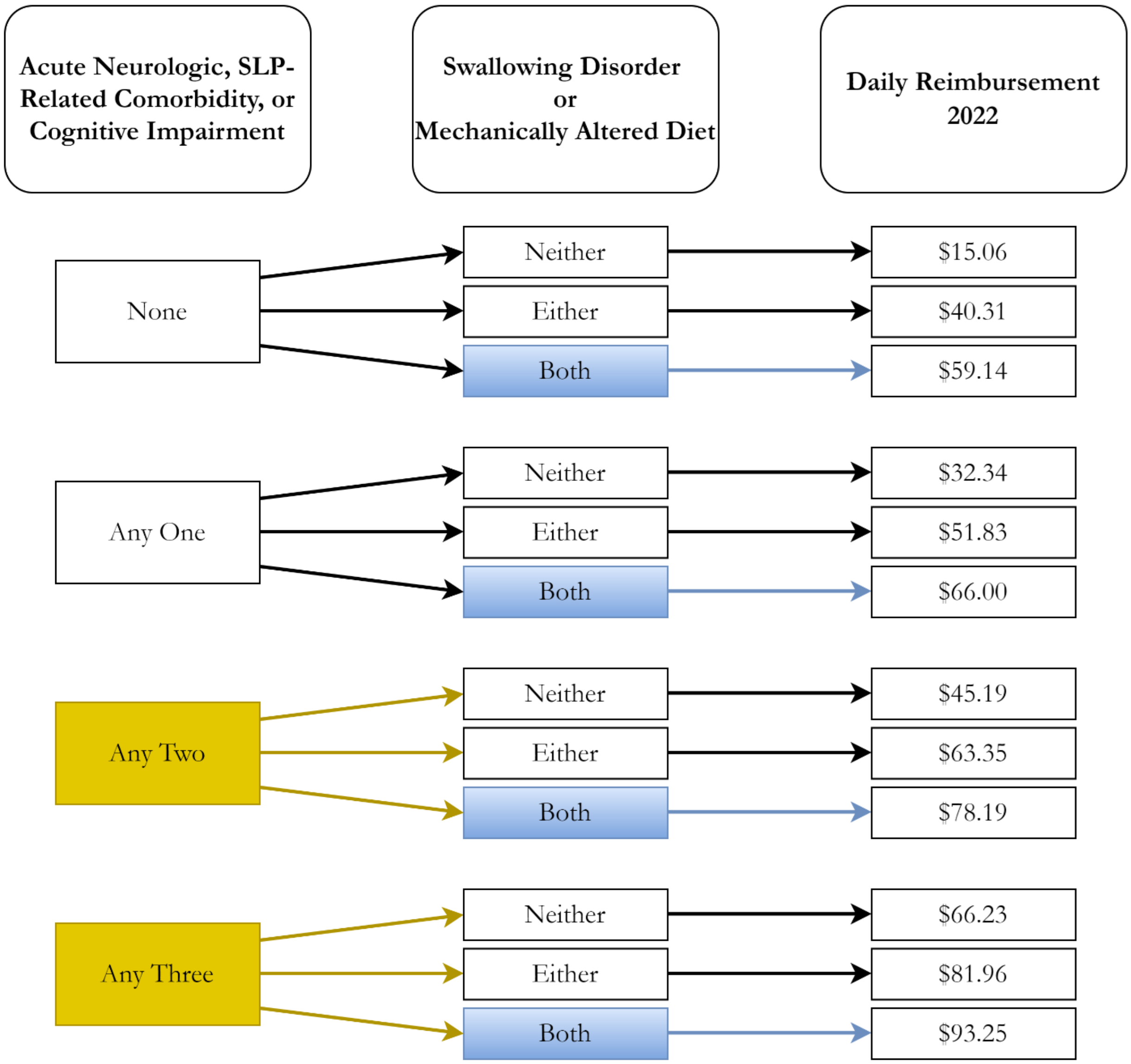
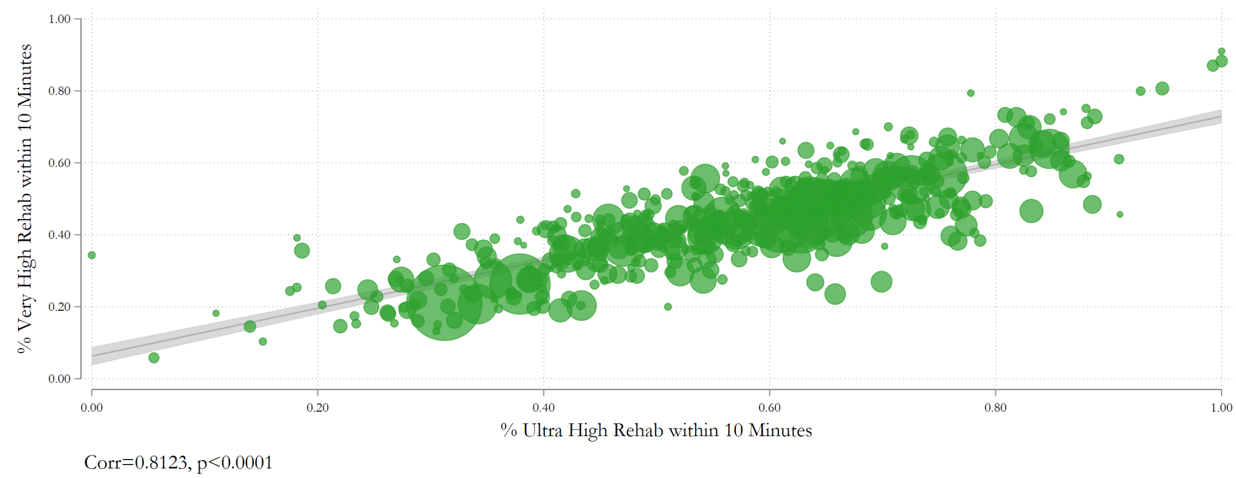


Figure IA.1. Excess Rehab and Threshold Treatment

This figure explores the relationship between system excess rehab and the propensity to treat within a tight window around the cutoff. Panel A displays a scatter plot between a system's excess rehab and either the proportion of all days billed between 720-729 minutes (left subgraph) or the proportion of all days billed more than 730 minutes (right subgraph). Each observation is an SNF system, and the size corresponds to the number of patients treated by each system. Panel B presents a scatter plot of the proportion of Ultra-High rehab patients billed within 10 minutes of the threshold against the proportion of Very-High rehab patients billed within 10 minutes of the threshold (500-509 minutes per week) by system. Finally, Panel C displays the distribution of Ultra-High rehab care by system type and whether care falls within 10 minutes of the cutoff.

Panel A. Relationship Between Excess Rehab and Ultra-High Billing by Threshold

Panel B. System-Level Billing Across Threshold



Panel C. Threshold Billing by System Excess Rehab

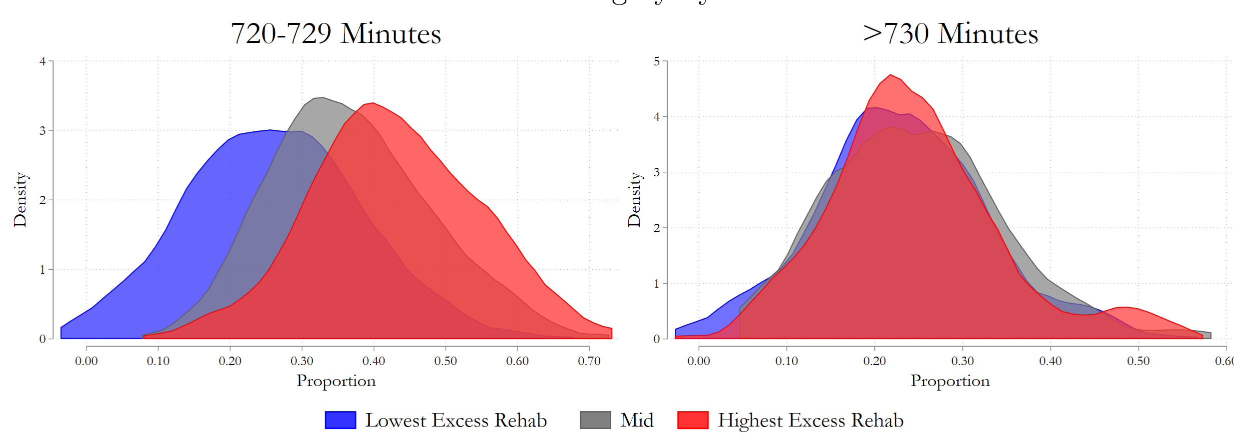


Figure IA.2. Use of Ultra-High Rehab for Expiring Patients

This figure explores the relationship between system excess rehab and the provision of Ultra-High rehab care for patients who die at a skilled nursing facility. The y-axis is the proportion of patients who received Ultra-High rehab care for every day that they were in the skilled nursing facility. The x-axis is a system's excess rehab as defined by Equation 1. The line denotes a binscatter that has been fit to the data. The t statistic is presented in the bottom left corner and standard errors are clustered at the SNF system level.

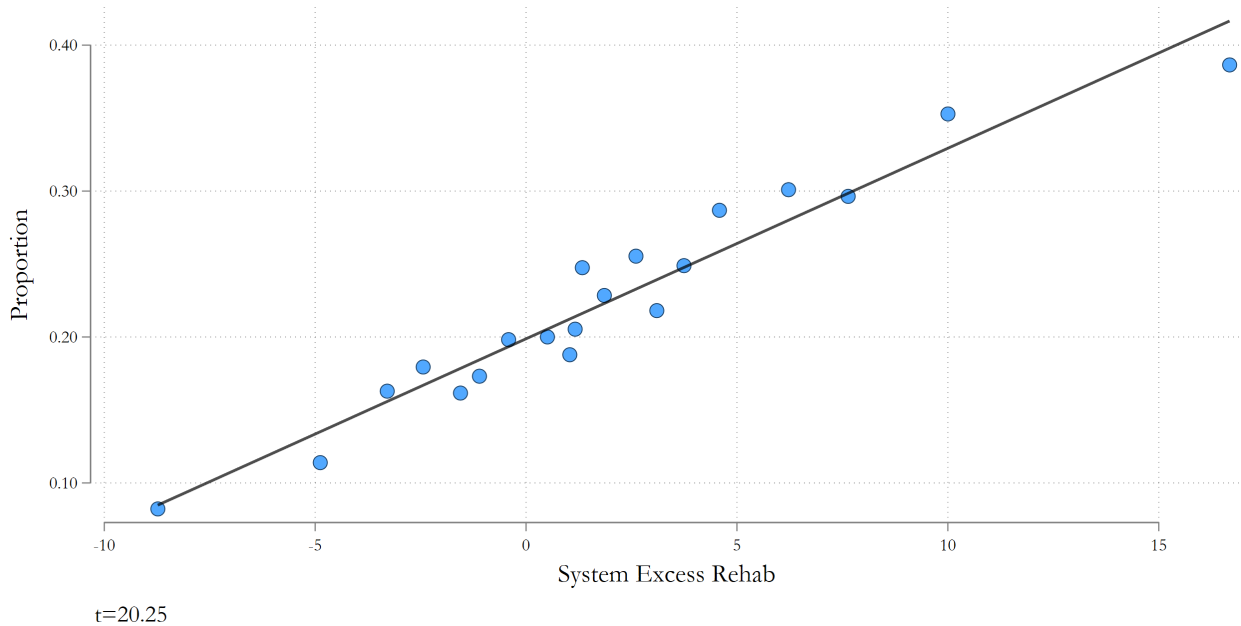


Figure IA.3. Excess Rehab and PDPM Coding Intensity by System

This figure explores billing practices under the RUG-IV and PDPM billing regimes. Each scatter plot denotes a patient diagnosis at the CCSR level. The x-axis displays the mean number of Ultra-High rehab days (left panel) or PDPM coding intensity (right panel) by opportunistic systems. Opportunistic SNF systems are those in the top tercile of excess rehab as measured using Equation 1. The y-axis displays the mean number of Ultra-High rehab days (left panel) or PDPM coding intensity (right panel) that patients with the same inpatient diagnosis receive at other facilities. Red denotes diagnosis groups for which patients receive higher Ultra-High rehab or higher coding intensity at opportunistic systems.

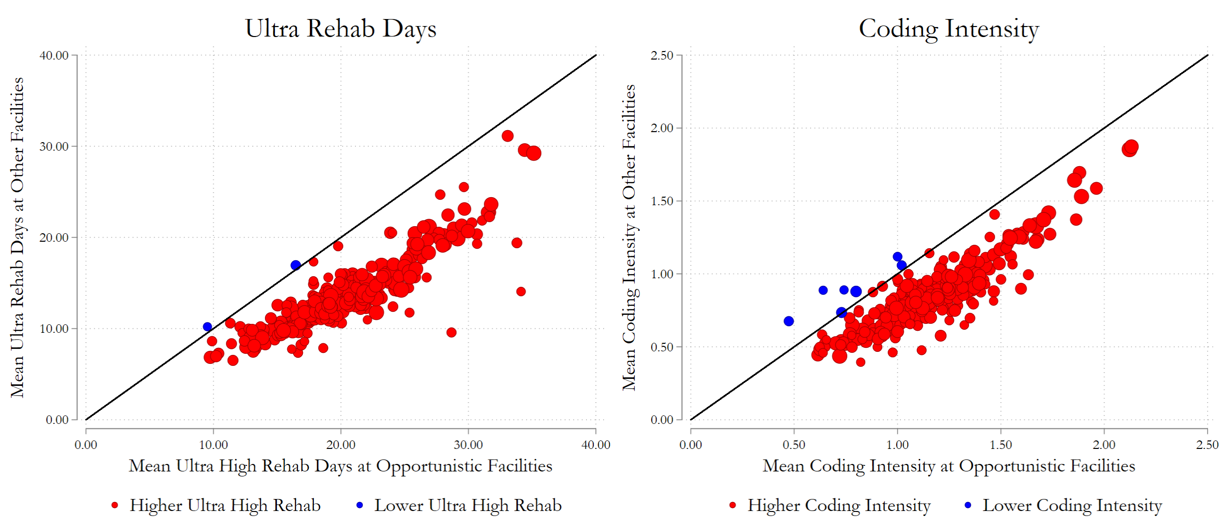


Figure IA.4. Persistence and Time-Series Variation in PDPM Coding Intensity

This figure explores the persistence and variation in PDPM coding intensity over time. *CodingIntensity* is the sum of indicators for whether a patient is classified as Low Function, Special Care High, Depression, SLP High or Dietary Restriction. *CodingIntensity* ranges from zero to five and a higher number denotes greater billing intensity. Panel A explores the persistence of PDPM coding intensity at the SNF system level by plotting the average PDPM coding intensity for the SNF system from 2019-2020 on the x-axis against the average coding intensity from 2020-2021 on the y-axis. Size of the markers denotes the system size. Red markers denote systems that experienced an increase in coding intensity during the second half of the sample. The correlation coefficient is presented at the bottom left. Panel B explores the time-series variation in coding intensity. Coding intensity is residualized on fixed effects for patient gender, age, race, and diagnosis at the CCSR-level as documented at the referring hospital. SNF systems are sorted into terciles based on their excess rehab from January 1, 2016-September 30, 2019.

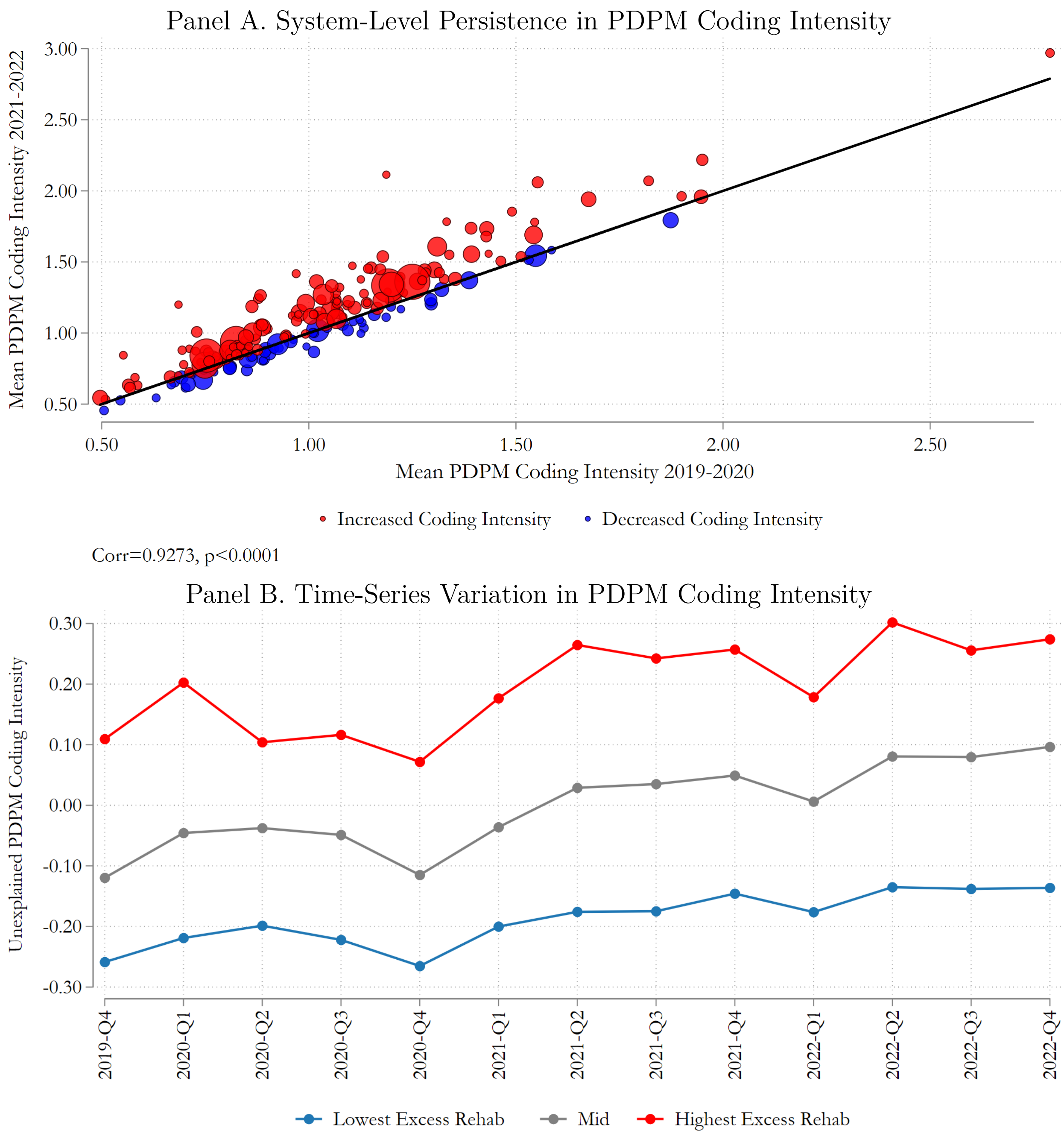


Figure IA.5. Acute Neurologic Diagnoses Around Regime Change

This figure plots the cross-sectional relationship between system excess rehab and the probability of Acute Neurologic primary diagnoses under RUG-IV (January 1, 2016-September 30, 2019) and under PDPM (October 1, 2019-December 31, 2022). System Excess Rehab is determined by the System fixed effect as in Equation 1. A binscatter is fitted separately for RUG-IV (green) and PDPM (blue).

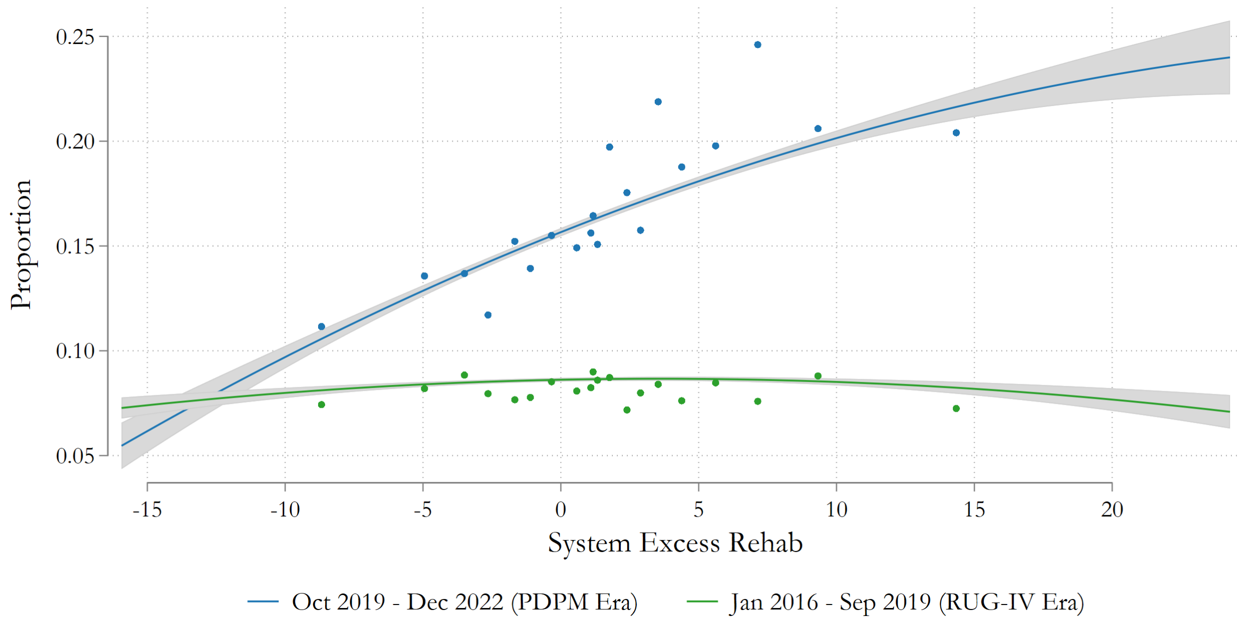


Figure IA.6. Change in Billing Intensity around Acquisition by Individual Category

This figure investigates the incidence of billing intensity around acquisition by Opportunistic Systems. Specifically, this figure displays coefficients from the following dynamic stacked cohort difference-in-difference regression:

$$Y_{ijt} = \alpha + \sum_{t=1}^{T} \beta_t Period_t \times AcquiredOpportunistic_j + \Gamma_{jc} + \delta_{tc} + \epsilon$$

where Y_{ijt} is an indicator for each individual billing category. $AcquiredOpportunistic_j$ is an indicator variable equal to one if a facility was acquired by an opportunistic SNF system, defined as systems in the highest tercile of excess rehab during RUG-IV. $Period_t$ is an indicator denoting time relative to acquisition. Confidence intervals denote 95% levels. Γ_{jc} is a facility by cohort fixed effect and δ_{tc} is a quarter by cohort fixed effect.

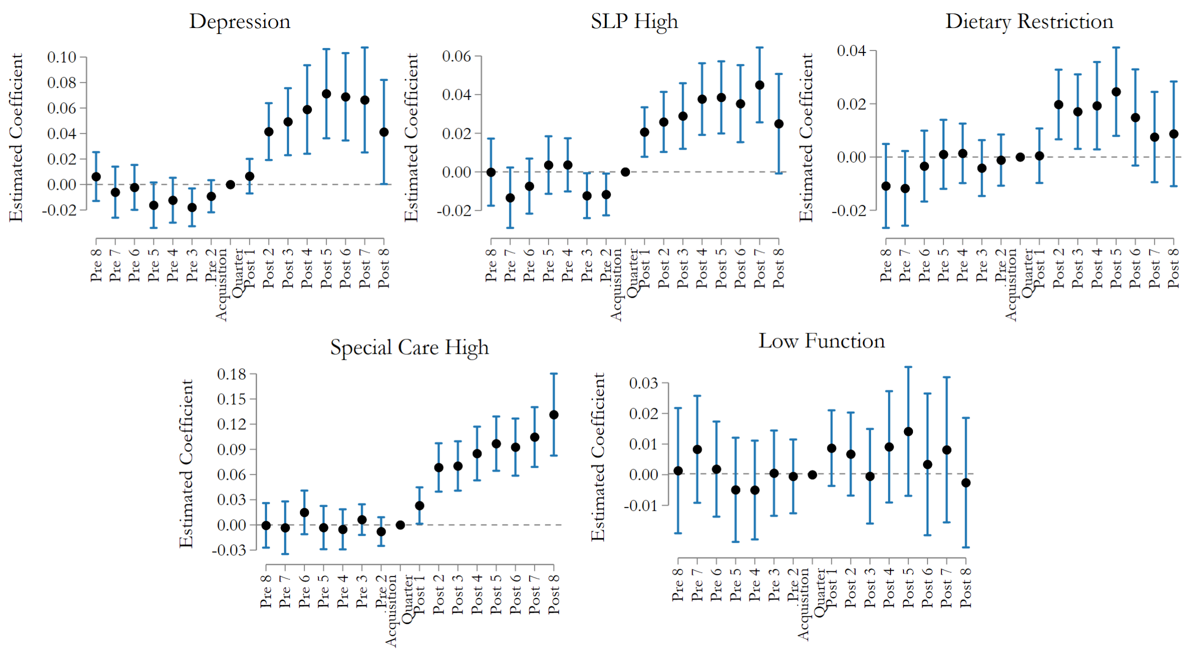


Figure IA.7. Competitor Occupancy and Probability of Admission

This figure visually demonstrates the effect of occupancy constraints on facility selection. Competitor occupancy is the occupancy rates of other facilities within the same Hospital Service Area (HSA) in the month prior to SNF admission. The y-axis shows the probability that a patient i chooses a given facility j within HSA h. All facilities located within the same HSA are considered as candidate facilities. The data is fit using a local polynomial specification.

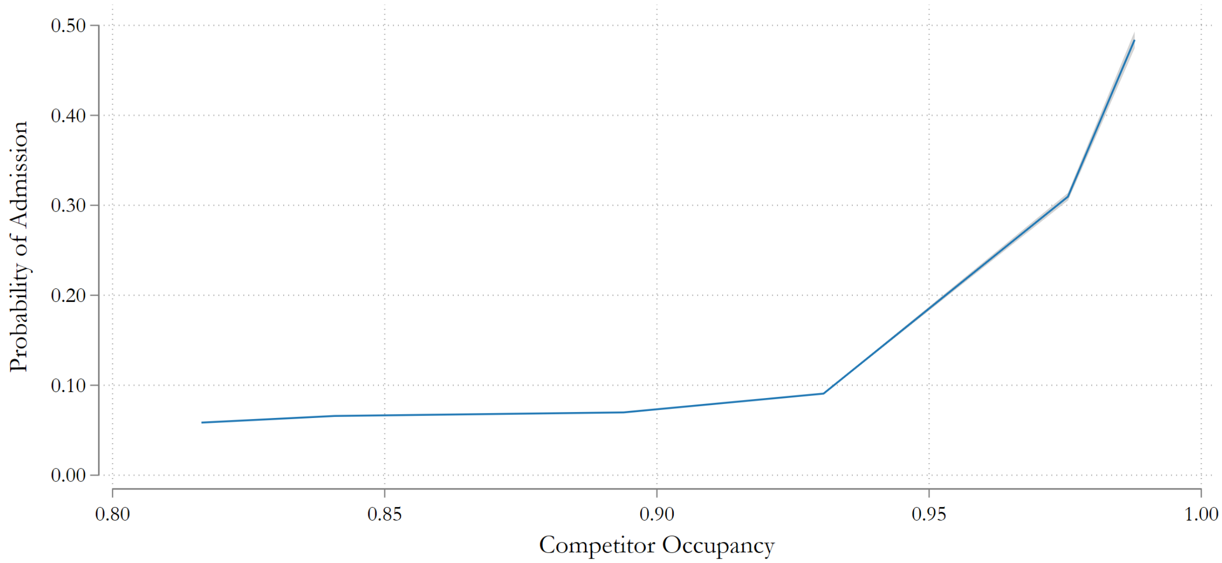
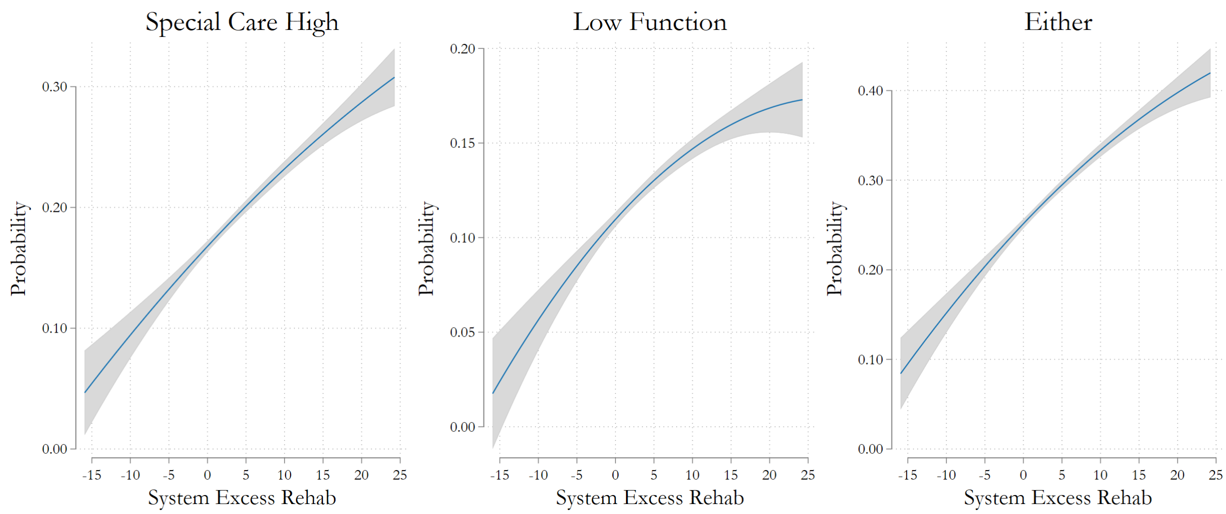


Figure IA.8. Within-Patient Billing Codes

This figure examines the potential fraudulent classification of patients by testing the likelihood that patients who were billed as receiving Ultra-High rehab care for every day of care under RUG-IV era that are subsequently coded as being low mobility patients with a categorization of Special Care High or Low Function once PDPM billing takes effect. Only those patients who were in a facility at the time of billing switch (October 1, 2019) are included. The graph shows a quadratic fit of the variable of interest and excess rehab. 95% confidence intervals are denoted by the grey shaded area. Special Care High is shown in the leftmost subgraph, Low Function, in the middle, and a category for either is presented in the far right subgraph. Panel B displays the change in probability that a patient is billed for a particular billing category after beginning a new SNF stay. Green denotes instances in which a patient's new stay is at a facility with lower excess rehab, while red denotes instances in which a patient's new stay is at a facility with higher excess rehab. For reference, blue is when a patient returns to the same facility.

Panel A. Low Mobility Classification among Ultra-High Rehab Patients



Panel B. Within-Patient Billing Categories following Facility Change

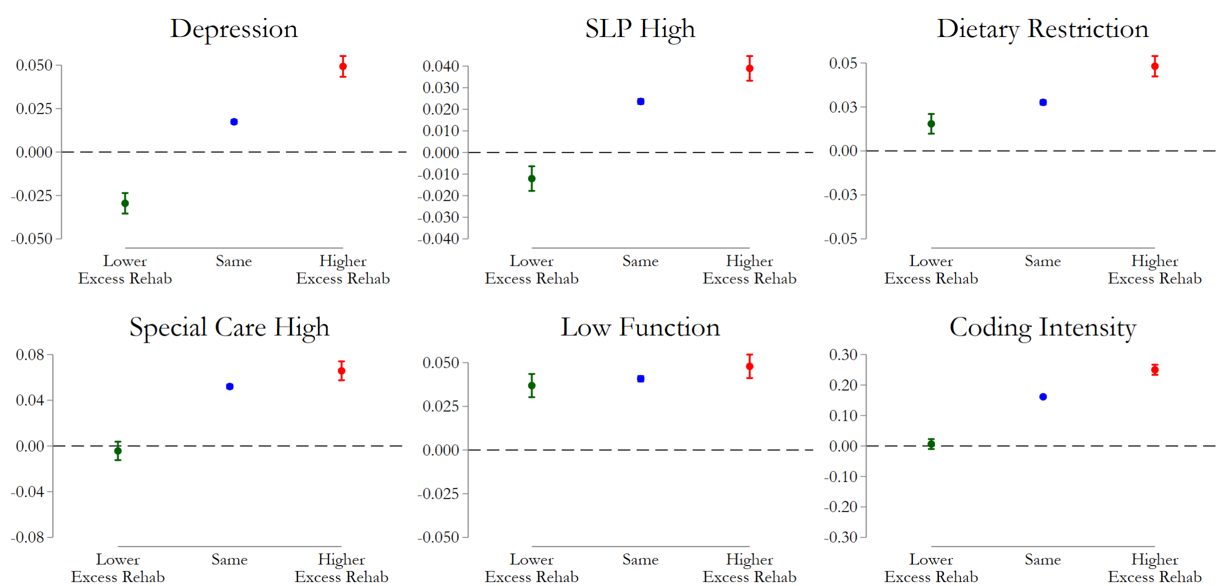
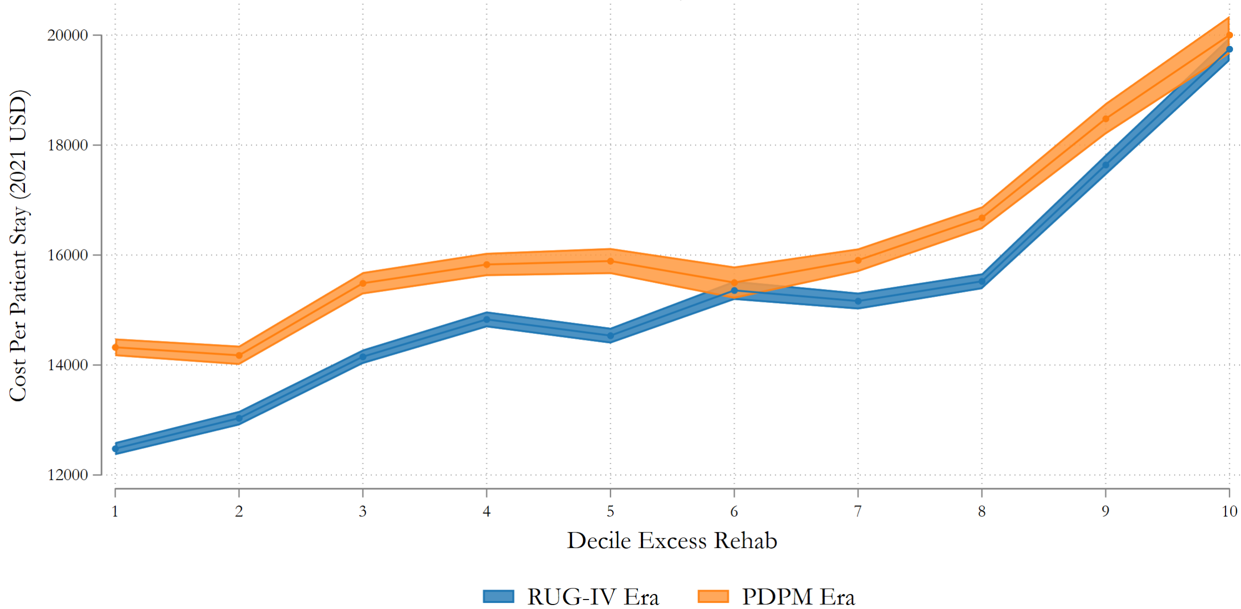


Figure IA.9. SNF Billing Practices and Cost of Patient Care

This figure explores the costs of skilled nursing care per patient stay. We compute this amount as the total of the Medicare allowed amount which includes the sum that Medicare pays, deductible or coinsurance amounts that the beneficiary is responsible for, and any amount owed by a third party divided by the total count of SNF stays provided. SNF systems are sorted into deciles of excess rehab which is defined according to Equation (1). The blue line denotes revenue during RUG-IV while the orange line denotes revenue during PDPM. The shaded areas denote 95% confidence intervals. In Panel B, a scatter plot of billing per patient stay against during RUG-IV (left subgraph) or PDPM (right subgraph) against system excess rehab is presented along with a linear fit and 95% confidence intervals. The correlation coefficient is presented at the bottom left corner of each subgraph. Revenue is adjusted for inflation to 2021 dollars.

Panel A. SNF Total Revenue by Decile Excess Rehab



Panel B. SNF Excess Rehab and Patient Revenue at the System Level

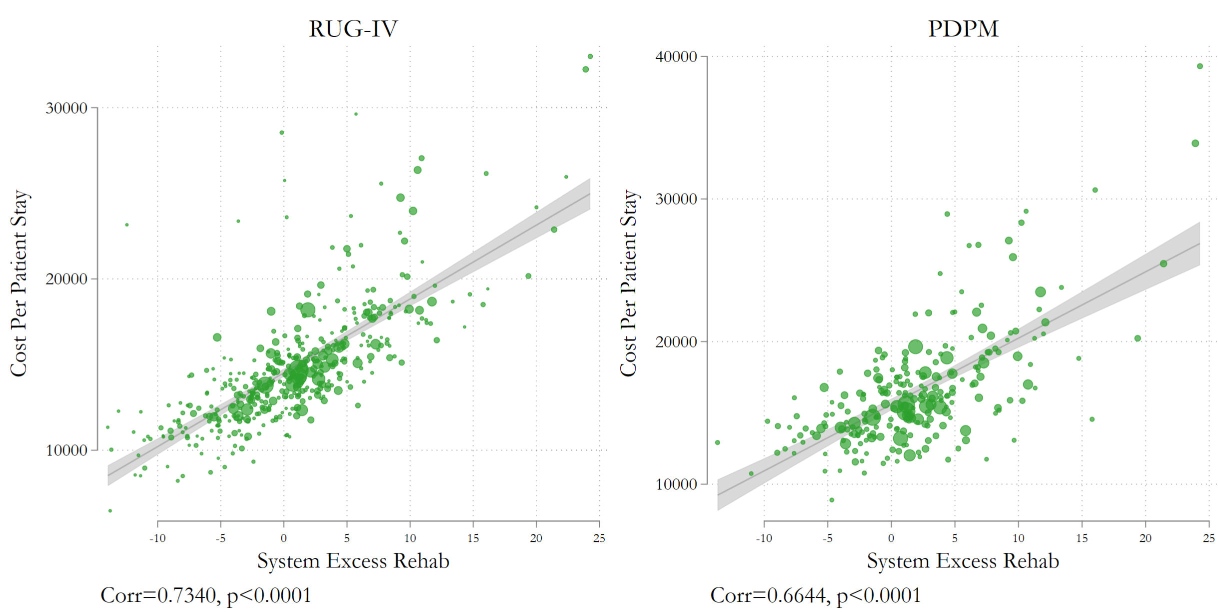


Figure IA.10. Patient Review Satisfaction and System Excess Rehab

This figure investigates whether patients at systems with higher levels of excess rehab report experiencing a higher quality of care using patient reviews collected from Caring.com. System excess rehab is determined by the system fixed effect in Equation 1. The figure plots a binscatter of either review stars (left subgraph) or the text sentiment (right subgraph) against system excess rehab levels.

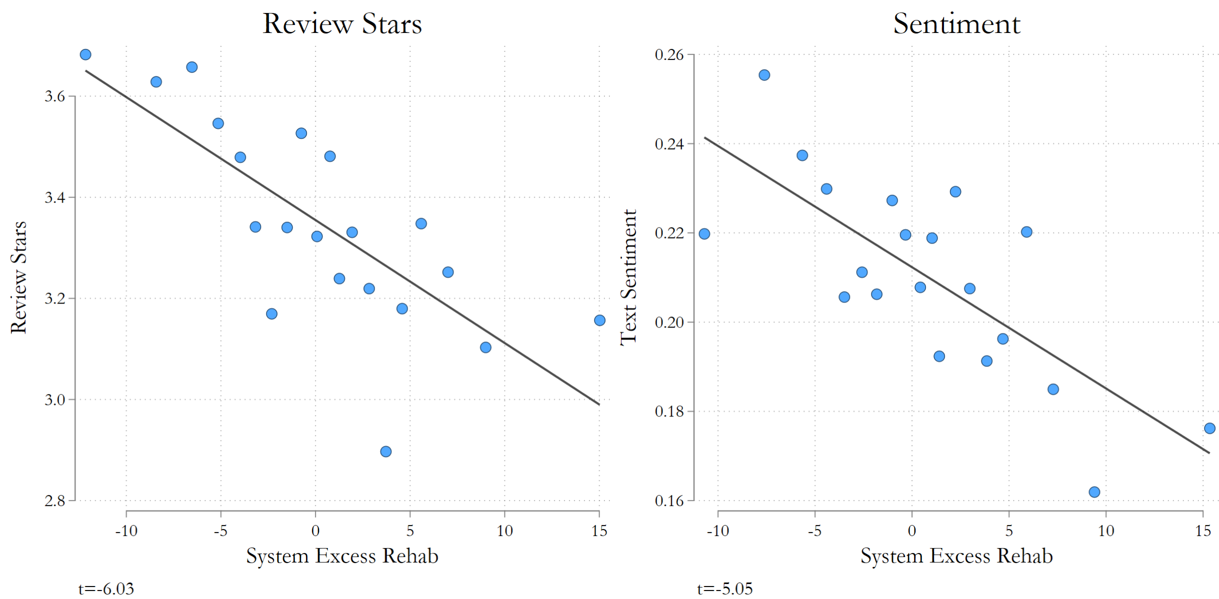


Figure IA.11. Nurse Staffing Hours

This figure investigates whether patients at systems with higher levels of excess rehab receive different levels of nursing care. This figure displays a binscatter of a regression of staffing hours per resident day by nursing type against system excess rehab. Because some states have different minimum nursing requirements, we include a county and state $\times$ year fixed effect for nurse staffing regressions.

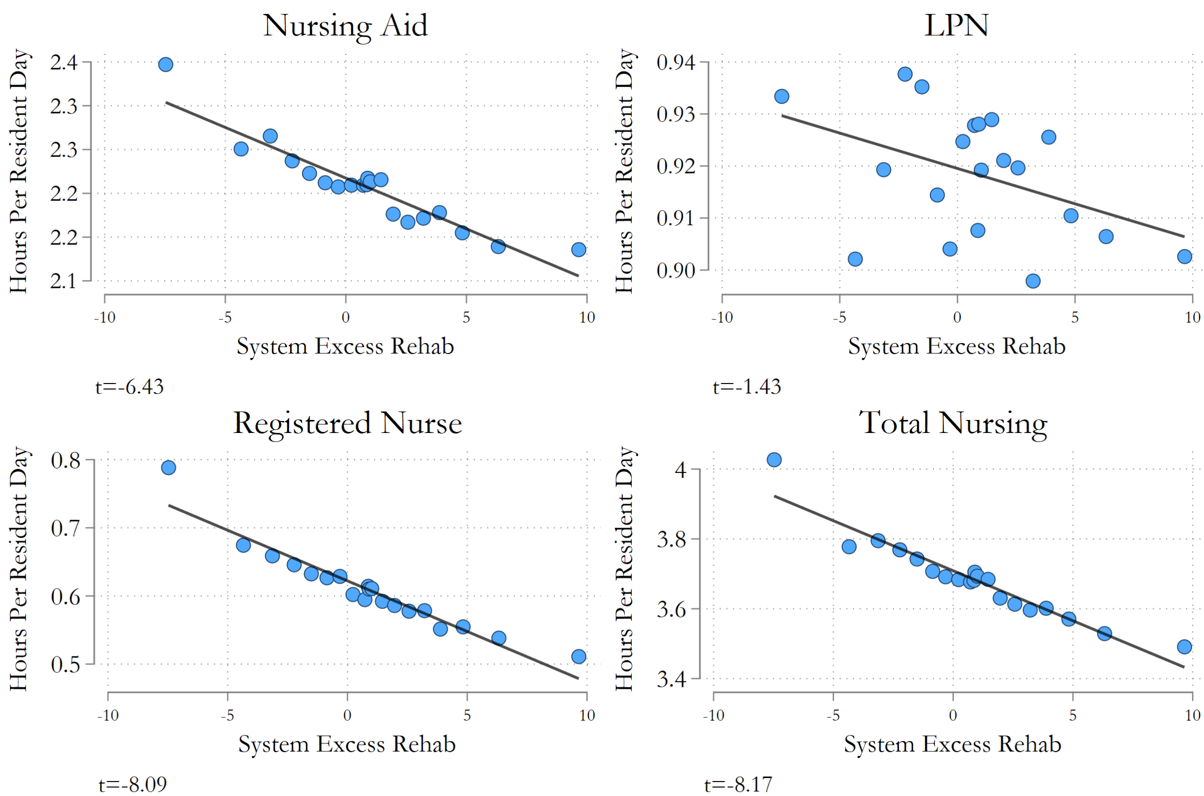


Figure IA.12. System Excess Rehab and Health Deficiencies

This figure explores the relationship between SNF system-level excess rehab and health deficiencies as documented at unannounced health inspections. Binscatters regressing the outcome variable of interest are plotted. Fixed effects are included for county and state × year. The outcome variables vary by panel. Inspection rating ranges from one star (worst) to five stars (best). Weighted deficiencies is the weighted sum of deficiencies found during health inspections. Weights come from CMS and more serious infractions are given heavier weights. Complaints is the amount of consumer complaints that are validated by state agencies during health inspections. Fine count is the total number of fines received by an individual SNF facility.

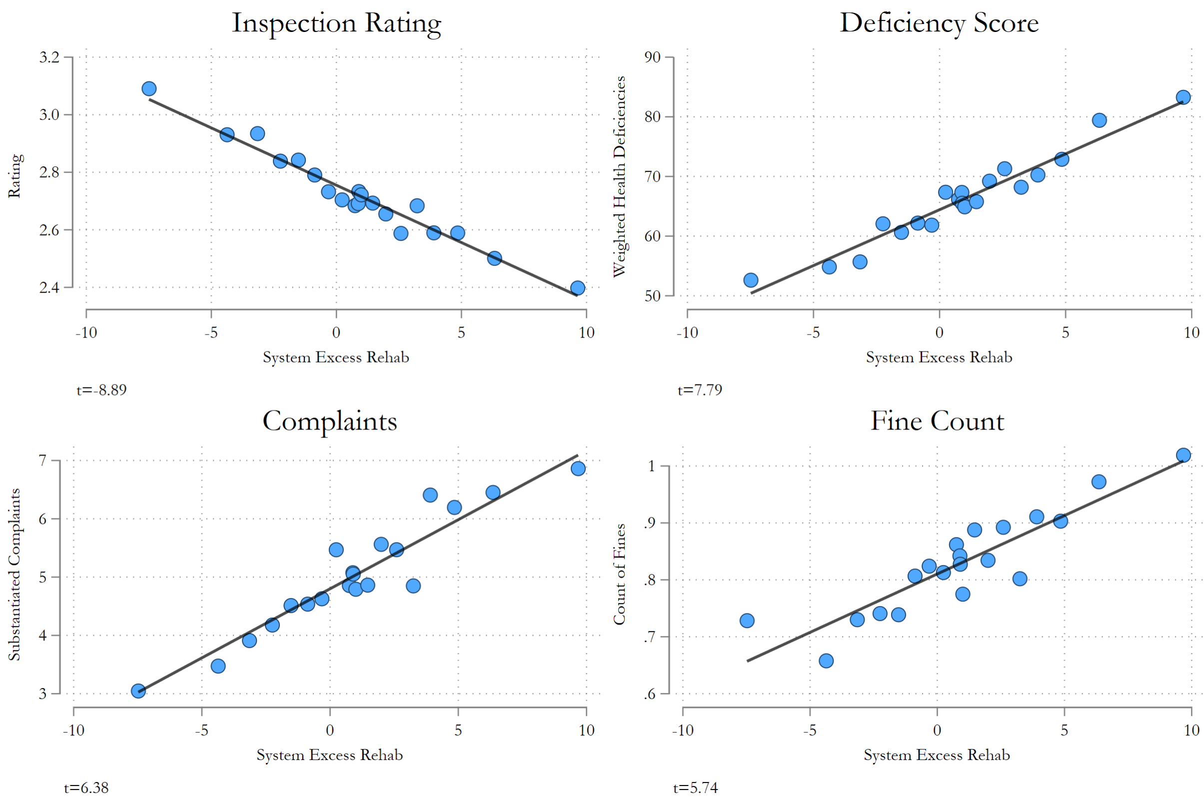


Figure IA.13. Preventable Health Outcomes-Pressure Ulcers

This figure investigates whether patients at systems with higher levels of excess rehab are more likely to develop pressure ulcers. Panel A explores the relationship between development of a pressure ulcer and SNF system excess rehab levels. A patient is identified as having developed a pressure ulcer while in a SNF if they are admitted to a hospital within two days of discharge and have developed a pressure ulcer. Panels B and C investigate potential underreporting of pressure ulcers by comparing our lower bound with the publicly reported quality measure. We consider a given quarter to be Highly Underreported if the lower bound we construct exceeds the publicly reported quality measure by at least 100%. Panel B presents a Binscatter and Panel C presents a scatter plot at the SNF system level.

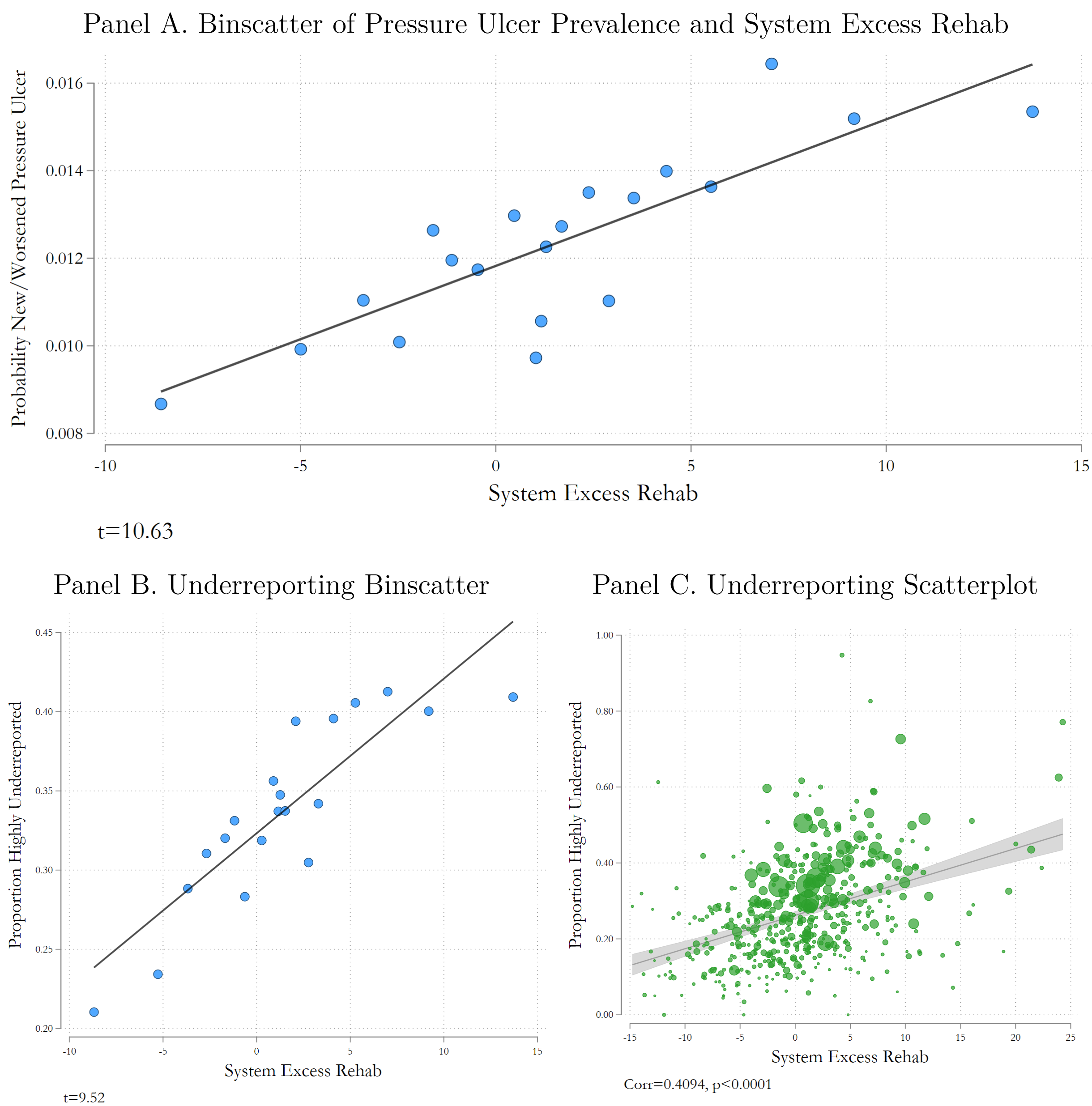


Figure IA.14. External Validation of Computed Outcomes

This figure explores the relationship between our calculated measure of short-stay pressure ulcers and the experience of pressure ulcers by SNF patients as captured by reviews on Caring.com. This figure explores the probability of a review mentioning pressure ulcers, as captured by the keywords “bed sore”, “pressure sore”, “pressure ulcer” as well as spelling and grammatical variations of these words. The leftmost subgraph explores the relationship between the likelihood of pressure ulcer reviews and the publicly reported pressure ulcer quality metric. The rightmost subgraph explores the relationship between reviews mentioning pressure ulcers and our calculated lower bound.

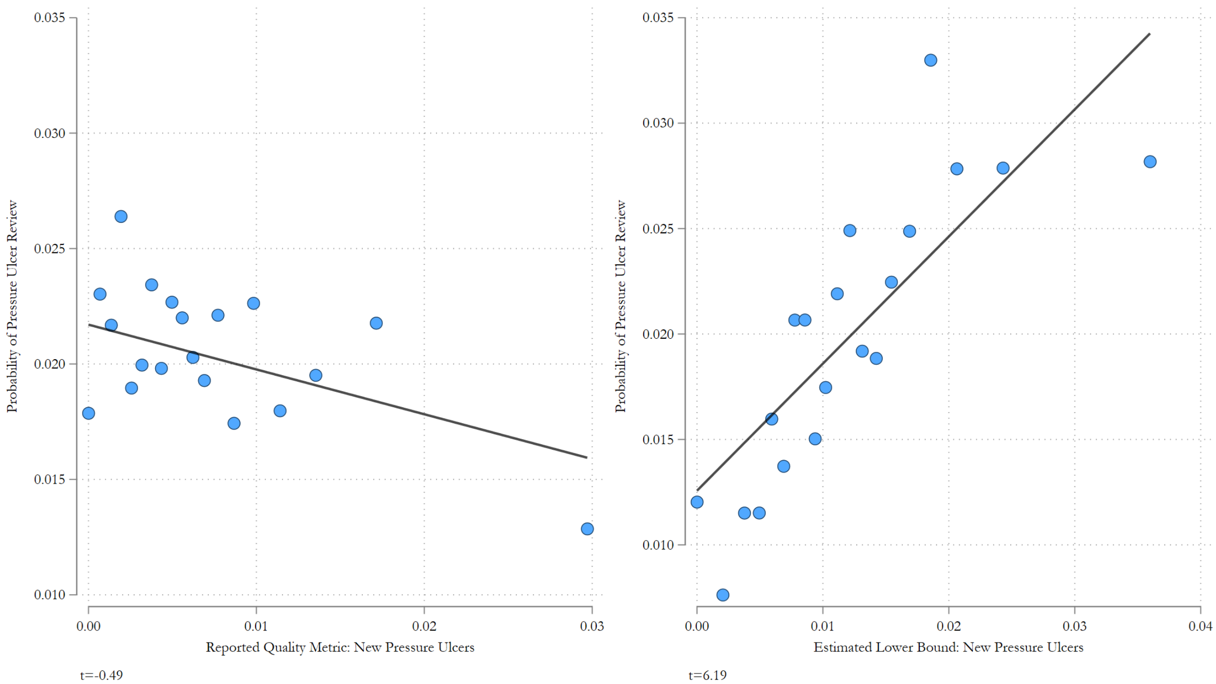


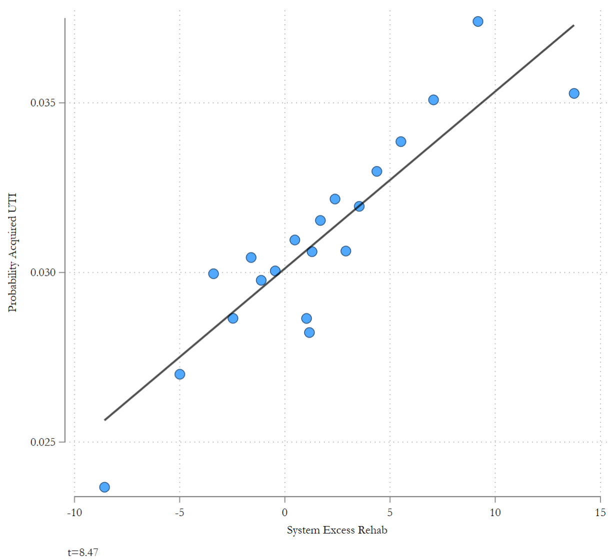
Figure IA.15. Preventable Health Outcomes-UTI and Traumatic Fall

This figure explores the incidence and potential underreporting of UTIs and traumatic falls by SNF systems. This figure presents a binscatter of the following OLS regression:

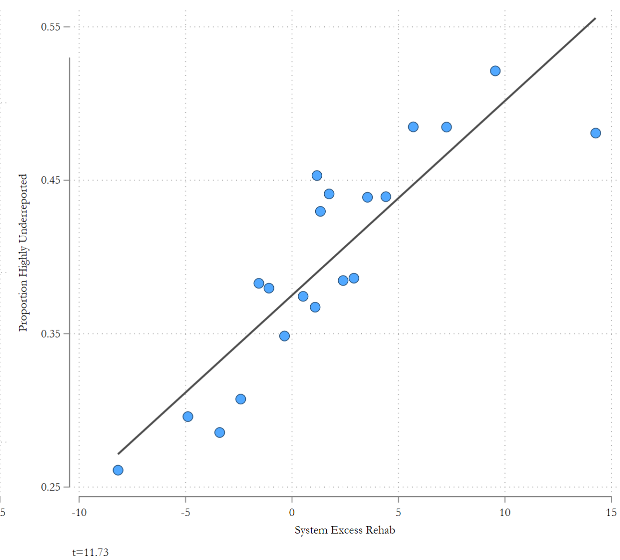
$$Y_{jt} = \alpha + \beta_1 ExcessRehab_j + \epsilon$$

Y_{jt} is either the incidence a UTI (Panel A) or traumatic fall (Panel C). In Panels C and D, we consider potential underreporting of quality metrics. We define a given quarter to be underreported if the lower bound we construct exceeds publicly reported quality measures by at least 100%.

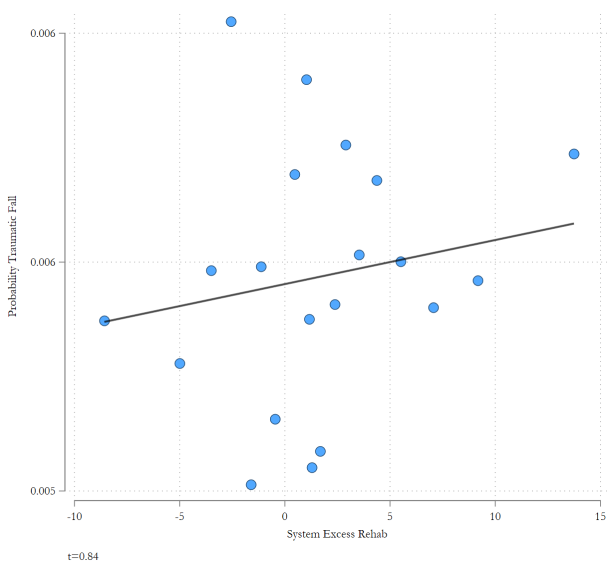
Panel A. Facility-Acquired UTI



Panel B. Potential Underreporting UTI



Panel C. Traumatic Fall at Facility



Panel D. Potential Underreporting Fall

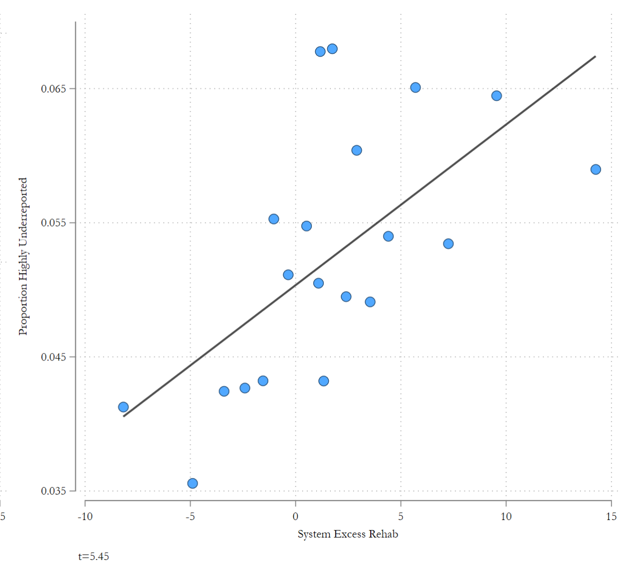
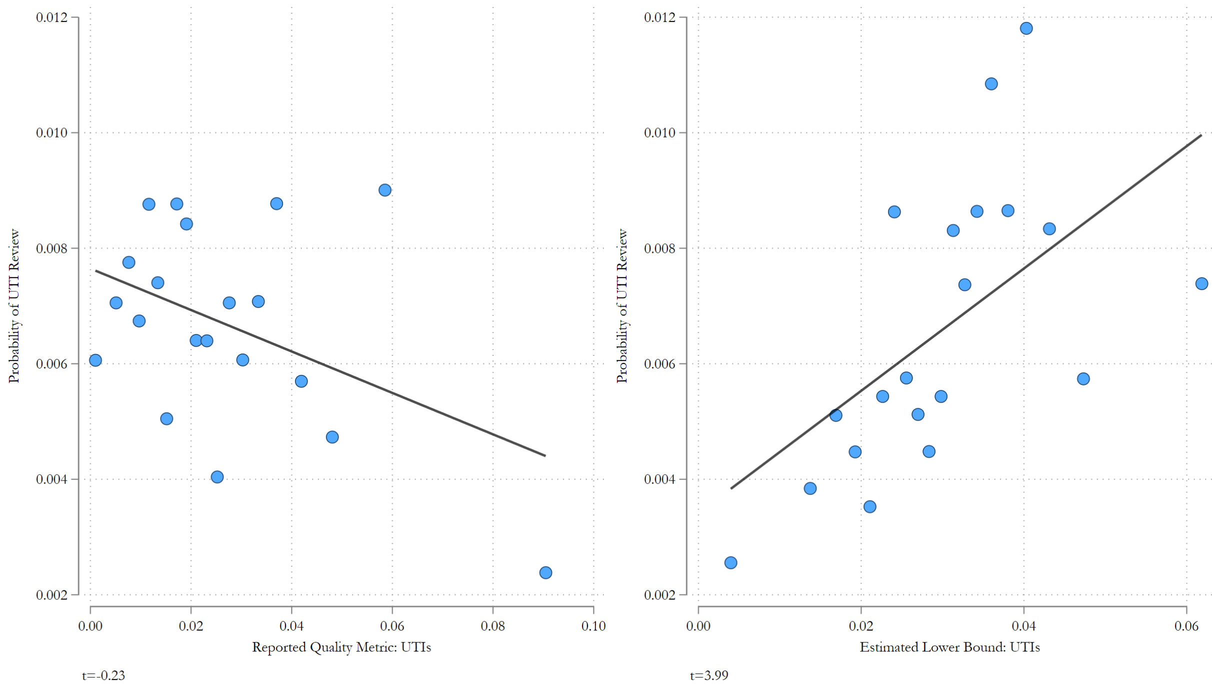


Figure IA.16. External Validation of Computed Outcomes-UTIs and Long Stay Fall

This figure explores the relationship between our calculated measure of UTI development of traumatic falls among SNF patients as captured by reviews on Caring.com. This figure explores the probability of a review mentioning Urinary Tract Infections or describing falls that occurred at the facilities. The leftmost subgraph explores the relationship between the likelihood of a review indicating a given condition and the corresponding publicly reported quality measures while the rightmost subgraphs explore the relationship between relevant reviews and our calculated lower bound.

Panel A: Validation of UTI



Panel B: Validation of Falls

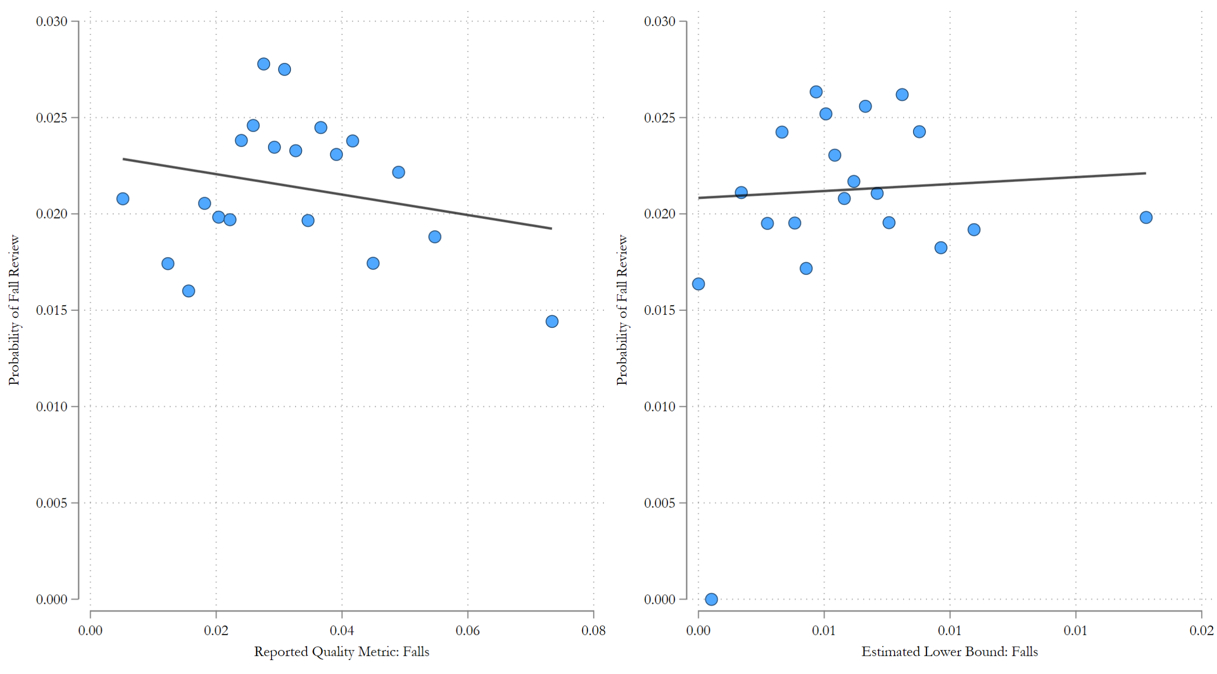


Figure IA.17. Customer Retention and Excess Rehab Levels

This figure investigates whether reputation is important to skilled nursing facilities by testing whether patients discipline facilities with reduced repeat business. Conditional on having at least one follow-up SNF visit, we examine the probability that a patient returns to the previous facility. Facilities are sorted into deciles of excess rehab, which is measured at the system level using Equation (1). Decile 10 is the highest level of excess rehab.

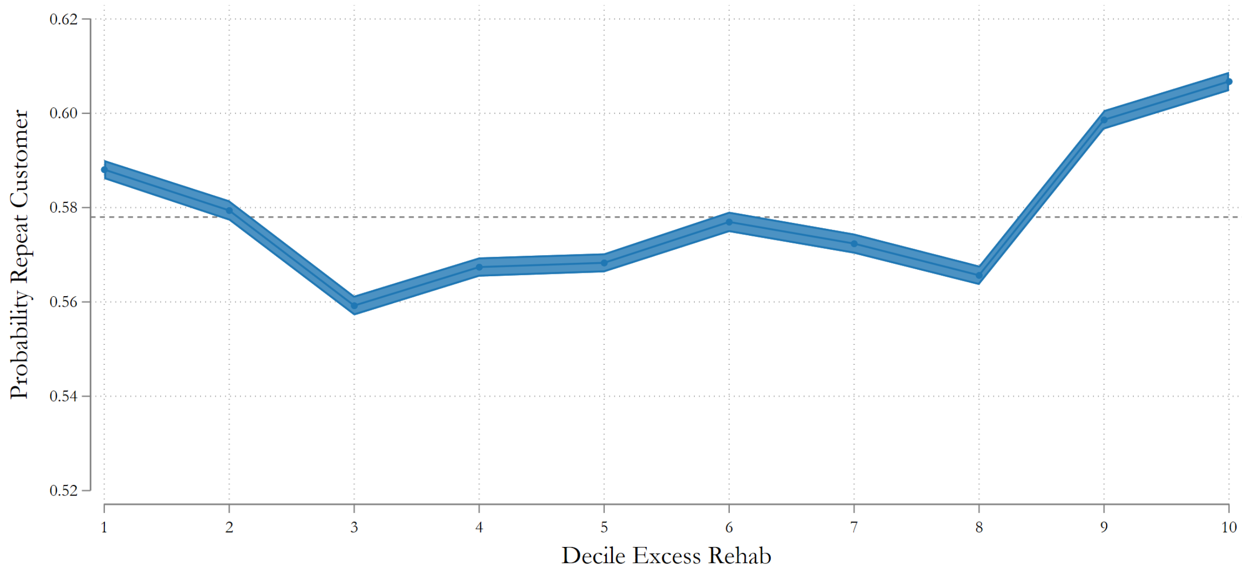
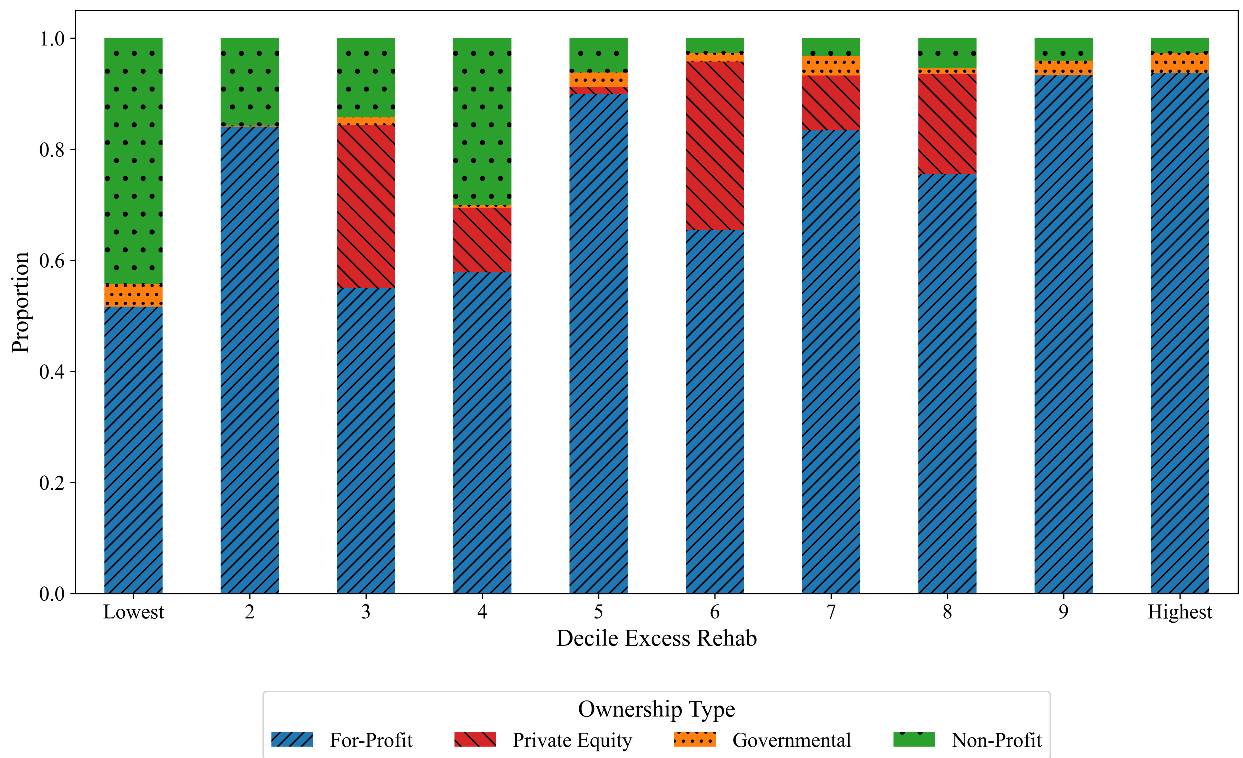


Figure IA.18. Billing Practices by Organizational Type

This figure investigates the relationship between billing practices and form of ownership. Facilities are sorted into deciles based on the unexplained Ultra-High rehab (Panel A) or the unexplained PDPM coding intensity (Panel B). The bars show the ownership type within each decile of billing intensity. Blue striped bars represent for-profit facilities excluding systems with private equity (PE)-backing. Red striped bars denote facilities that are operated by SNF systems with PE-backing. Orange dotted bars denote governmental facilities, while green bars denote non-profit facilities.

Panel A. SNF Ownership by Decile of Excess Rehab (RUG-IV)



Panel B. SNF Ownership by Decile of PDPM Coding Intensity

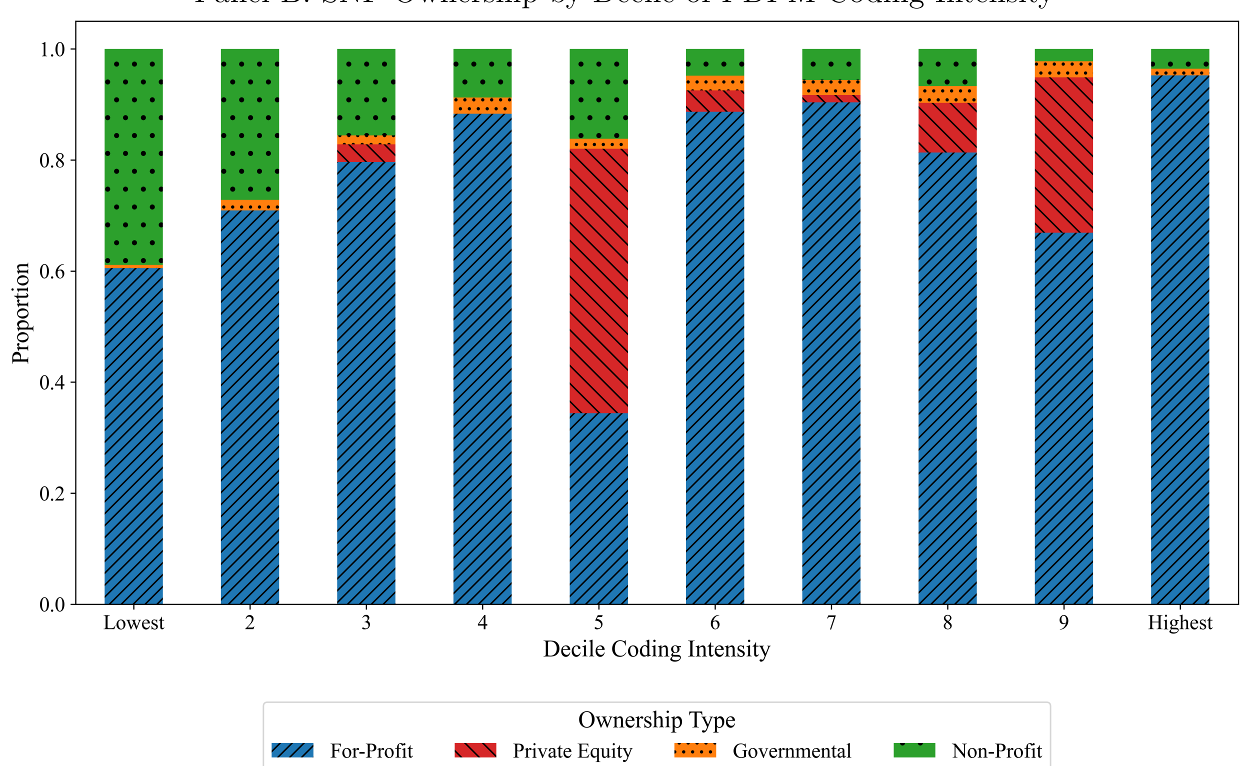
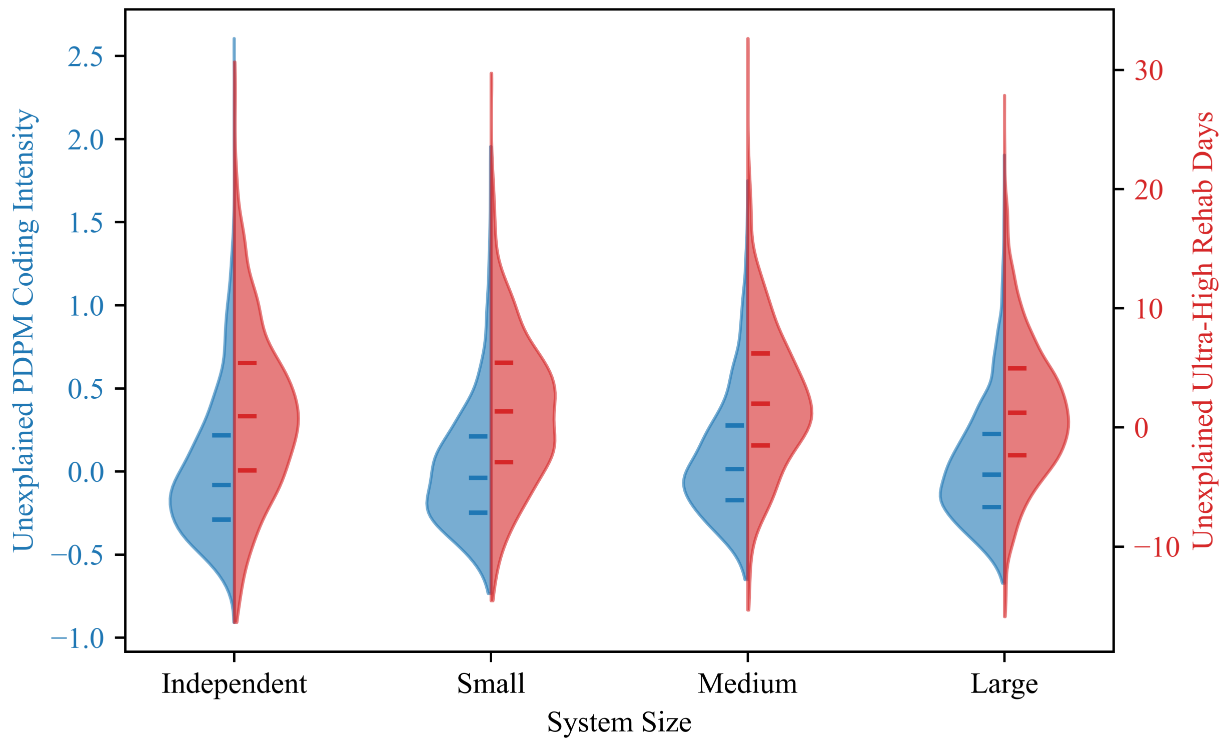


Figure IA.19. SNF System Size and Billing Practices

This figure explores the relationship between SNF system size and billing practices. Skilled nursing facilities are classified into groups based on the overall number of facilities operated by the system. Independent denotes facilities that do not belong to any system. Small systems are systems with 2-10 facilities, while medium systems have between 11-25 facilities. Finally, large systems operate more than 25 facilities. Unexplained PDPM coding intensity is denoted by the left axis while unexplained Ultra-High rehab days is denoted by the right axis. For-profit facilities are featured in Panel A and non-profit facilities are featured in Panel B.

Panel A. SNF Billing by System Size (For-Profit)



Panel B. SNF Billing by System Size (Non-Profit)

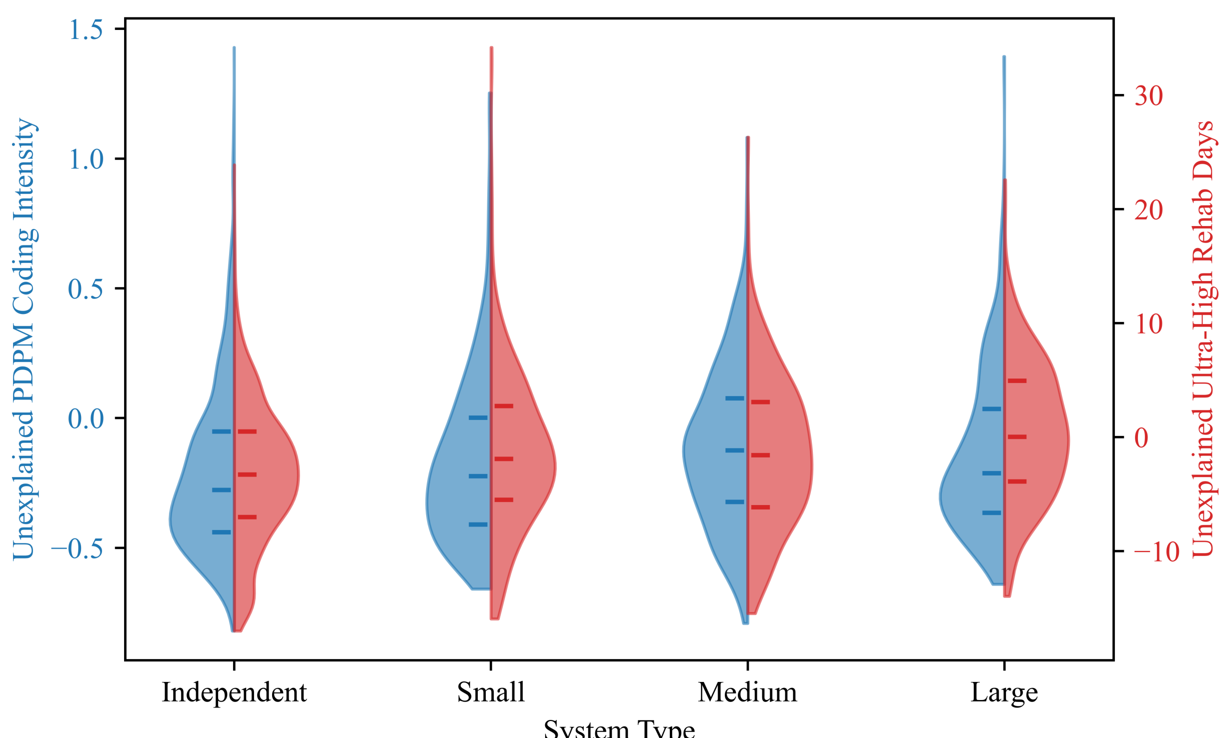
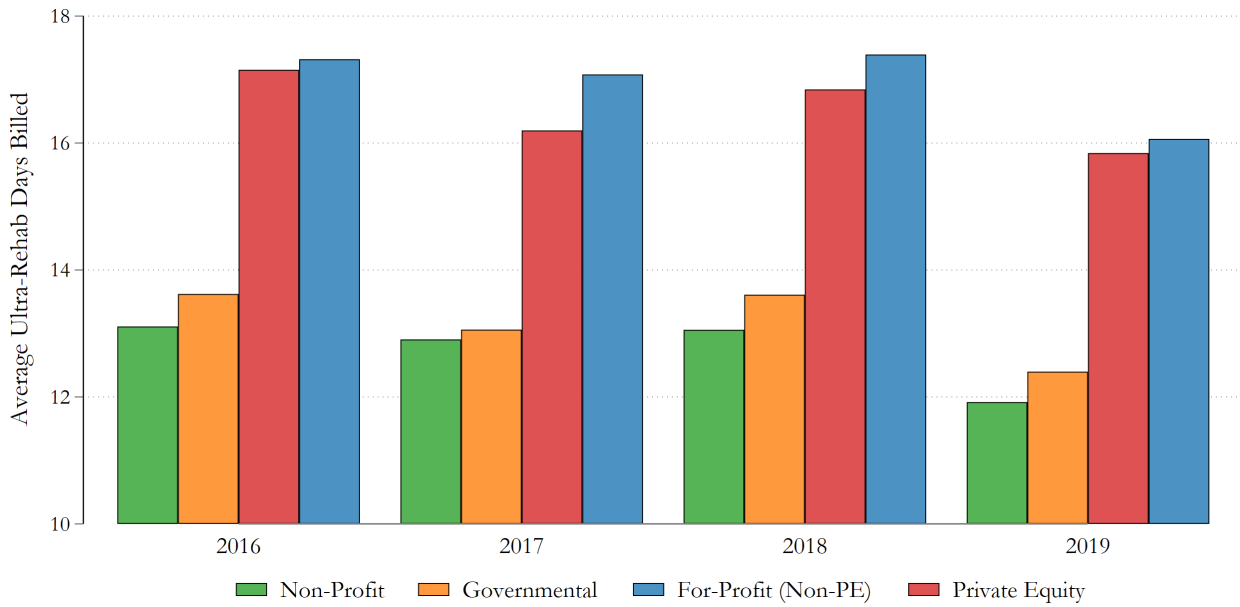


Figure IA.20. Billing Intensity by Ownership Type

This figure explores the relationship between ownership type and billing intensity under RUG-IV (January 1, 2016-September 30, 2019) and PDPM (October 1, 2019-December 31, 2022). The measure of billing for RUG-IV is the average number of Ultra-High rehab days billed, while the measure of billing for PDPM is coding intensity. Facilities are sorted into four categories of ownership: Non-Profit (denoted by green bars), Governmental (denoted by orange bars), For-Profit Non-Private Equity (denoted by blue bars), and Private Equity (denoted by red bars). The average number of Ultra-High rehab days billed by each system type for each year is presented in Panel A while the average coding intensity during PDPM is presented in Panel B.

Panel A. Average Ultra-High Rehab Days by Ownership Type



Panel B. Average PDPM Coding Intensity by Ownership Type

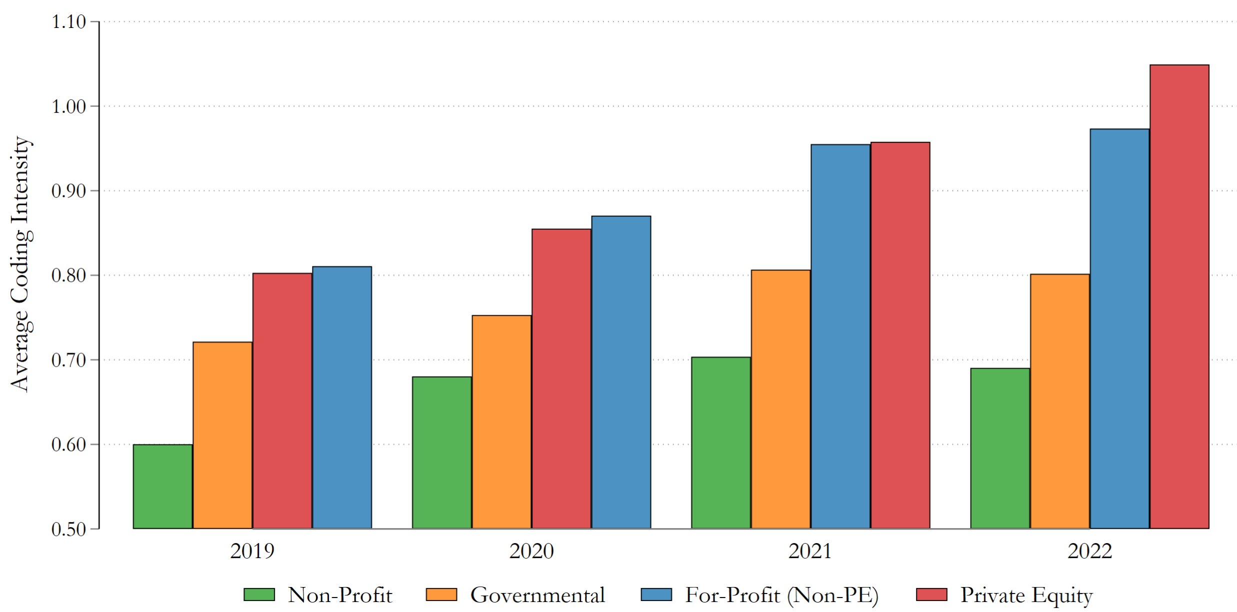


Table IA.I. Summary Statistics

This table presents summary statistics for our sample. The sample includes Medicare claims for skilled nursing facilities from January 1, 2016 to December 31, 2022. Data comes from the Skilled Nursing Facility Limited Data Set, which covers the universe of Medicare claims for skilled nursing. RUG-IV is an indicator variable equal to one for claims billed under the Resource Utilization Group IV era from January 1, 2016 to September 30, 2019. PDPM is an indicator equal to one for claims billed under the Patient Driven Payment Model from October 1, 2019 to December 31, 2022. "Unexplained" denotes that a variable was residualized on fixed effects for patient gender, age, race and diagnosis at the CCSR-level as recorded at the referring hospital. Ultra rehab days billed is the number of days for which therapy is billed at the highest level under RUG-IV. Coding intensity is computed only for PDPM era claims.

Panel A: Patient-Level Summary Statistics

	Mean	S.D.	P5	P10	P25	P50	P75	P90	P95
PDPM	0.42	0.49	0.00	0.00	0.00	0.00	1.00	1.00	1.00
RUG IV	0.59	0.49	0.00	0.00	0.00	1.00	1.00	1.00	1.00
Total Days Billed	26.59	21.94	3.00	5.00	11.00	20.00	35.00	57.00	75.00
Ultra Rehab Days	15.61	18.95	0.00	0.00	0.00	12.00	24.00	40.00	55.00
Coding Intensity	1.01	1.07	0.00	0.00	0.00	1.00	2.00	3.00	3.00
Unexplained Ultra Days	0.00	19.05	-20.13	-17.43	-14.59	-3.83	8.52	24.57	38.78
Unexplained Cod. Inten.	0.00	1.04	-1.26	-1.07	-0.86	-0.09	0.60	1.39	2.06
Dietary Restriction	0.13	0.34	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Special Care High	0.32	0.47	0.00	0.00	0.00	0.00	1.00	1.00	1.00
Low Function	0.24	0.43	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Depression	0.11	0.31	0.00	0.00	0.00	0.00	0.00	1.00	1.00
SLP High	0.21	0.41	0.00	0.00	0.00	0.00	0.00	1.00	1.00
Observations	14,319,390								

Panel B: Facility-Level Summary Statistics

	Mean	S.D.	P5	P10	P25	P50	P75	P90	P95
Total Days Billed	27.47	7.61	16.13	19.25	22.87	26.86	31.76	37.03	40.62
Ultra Rehab Days	14.05	8.08	0.16	2.34	8.65	14.13	19.19	24.08	27.40
Coding Intensity	0.92	0.39	0.40	0.49	0.65	0.87	1.13	1.42	1.64
Unexplained Ultra Days	-0.82	7.30	-13.13	-10.08	-5.52	-1.02	3.58	8.36	11.49
Unexplained Cod. Inten.	-0.08	0.36	-0.55	-0.48	-0.33	-0.13	0.12	0.39	0.60
Dietary Restriction	0.11	0.09	0.01	0.02	0.05	0.09	0.16	0.23	0.29
Special Care High	0.27	0.16	0.05	0.08	0.14	0.24	0.37	0.50	0.57
Low Function	0.25	0.11	0.09	0.12	0.17	0.23	0.31	0.38	0.43
Depression	0.09	0.12	0.00	0.00	0.01	0.04	0.10	0.23	0.35
SLP High	0.21	0.11	0.07	0.10	0.14	0.19	0.26	0.34	0.41
Observations	16,163								

Table IA.II. Excess Rehab and PDPM Billing–Individual Categories

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with billing intensity during the Patient Driven Payment Model (PDPM) era (October 1, 2019-December 31, 2022). We estimate an OLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a measure of billing intensity for patient i at facility j during quarter t and is an indicator for a patient being classified as either Low Function, Special Care High, Depression, SLP High or Dietary Restriction. Low Function, Special Care High, and Depression are classifications that impact the Nursing component of PDPM case-mix and increase reimbursement. SLP High and Dietary Restriction classification increase PDPM reimbursements for the SLP component (as shown in Exhibits 1 and 2). Patient controls include gender, age (in five-year increments), and race. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length refers to the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level.

	(1) Low Func.	(2) S.C.H.	(3) Depress	(4) SLP High	(5) Diet
Excess Rehab	0.00218***	0.00668***	0.00681***	0.00523***	0.00348***
	(5.73)	(5.59)	(5.71)	(11.44)	(6.93)
Patient Gender	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Length	Yes	Yes	Yes	Yes	Yes
Observations	3,855,593	3,855,593	3,855,593	3,855,593	3,855,593
Adjusted R^2	0.072	0.110	0.106	0.188	0.061

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.III. Instrumental Variables-First Stage

In this table, we present results for the first stage of the instrumental variables specification. We instrument for excess rehab faced by a patient by utilizing variation in occupancy levels of competing facilities. The instrument, $PredictedExcessRehab$ comes from a weighted average of excess rehab within a Hospital Service Area according to Equation 5. Weights derive from the occupancy levels of competing facilities according to Equation 4. We then estimate the first-stage with a regression of the form:

$$ExcessRehab_{ijt} = \alpha + \beta PredictedExcessRehab_{jt} + \theta X_i + FixedEffects + \epsilon$$

where $ExcessRehab_{ijt}$ is the excess rehab for facility j selected by patient i at time t. To control for time-invariant variation in excess rehab levels due to geographic concentration of SNF systems, we include a Hospital Service Area fixed effect in columns 1-3. Robust standard errors are clustered at the SNF system level and t statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Excess Rehab	0.418***	0.418***	0.389***	0.424***	0.424***	0.428***
	(10.58)	(10.57)	(11.51)	(10.78)	(10.79)	(11.00)
Quarter-Year FE	Yes	No	No	Yes	No	No
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis FE	Yes	No	No	Yes	No	No
County x Quarter FE	No	No	Yes	No	No	Yes
Diagnosis x Hospitalization Length	No	Yes	Yes	No	Yes	Yes
HSA FE	No	No	No	Yes	Yes	Yes
Observations	3,273,580	3,268,502	3,266,333	3,273,580	3,268,502	3266332
Adjusted R^2	0.415	0.415	0.613	0.765	0.765	0.776

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.IV. Instrumental Variables-Second Stage

In this table we examine the effect of excess rehab during RUG-IV on PDPM coding intensity. We estimate a 2SLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a measure of billing intensity for patient i at facility j during quarter t and is an indicator for a patient being classified as either Low Function, Special Care High, Depression, SLP High or Dietary Restriction. We instrument for $ExcessRehab_j$ using $PredictedExcessRehab$ from Equation 5, which is the predicted excess rehab a patient will face due to capacity constraints. Low Function, Special Care High, and Depression are classifications that impact the Nursing component of PDPM case-mix and increase reimbursement. SLP High and Dietary Restriction classification increase PDPM reimbursements for the SLP component (as shown in Exhibits 2 and 1). Patient controls include gender, age (in five-year increments), and race. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length refers to the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level. Kleibergen-Paap F statistics are at the bottom of each column.

	(1) Low Func.	(2) S.C.H.	(3) Depress	(4) SLP High	(5) Diet	(6) Cod. Intens.
Excess Rehab	0.00241***	0.00691***	0.00762***	0.00567***	0.00340***	0.0260***
	(3.45)	(5.18)	(5.47)	(11.93)	(5.25)	(7.75)
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Length	Yes	Yes	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Kleibergen-Paap F Statistic	120.96	120.96	120.96	120.96	120.96	120.96
Observations	3,266,332	3,266,332	3,266,332	3,266,332	3,266,332	3,266,332

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.V. Excess Rehab and Patient Health Outcomes at Hospital Versus Facility (2SLS)

In this table, we explore the validity of the instrument by relating $PredictedExcessRehab$ to patient health as measured at either the referring hospital or the skilled nursing facility.

$$y_{ijt} = \alpha + \beta PredictedExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

y_{ijt} is a measure of patient comorbidity for patient i admitted to facility j at time t. *Acute* is an indicator variable equal to one if a patient's primary diagnosis belongs to the Acute Neurologic diagnosis group. SLP-related is an indicator equal to one if any patient diagnosis is SLP-related. Finally, NTA is the sum of NTA-related comorbidities. Columns 1-3 denote the presence of these conditions at the referring hospital, while columns 4-6 denote the presence of these conditions at the skilled nursing facility. $PredictedExcessRehab$ is defined as in Table IA.III. Fixed effects are as indicated at the bottom of each column.

	Hospital Acute	Hospital SLP	Hospital NTA	SNF Acute	SNF SLP	SNF NTA
Predicted Excess Rehab	-0.000101***	-0.00000867	-0.000278	0.00182***	0.000792***	0.00317***
	(-2.61)	(-0.40)	(-0.62)	(5.97)	(4.86)	(4.27)
Quarter-Year FE	Yes	No	No	Yes	No	No
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,102,616	4,150,639	4,150,639	5,102,616	4,150,639	4,150,639
Adjusted R^2	0.004	0.006	0.075	0.028	0.020	0.069

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.VI. Excess Rehab and Patient Reclassification

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with patient reclassification after PDPM enactment. We estimate an OLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a measure of low patient mobility and is either the classification of Low Function or Special Care High. The sample included in this test is patients who were at a skilled nursing facility during the case-mix transition and for whom were billed as Ultra-High rehab for every eligible day under RUG-IV. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length is the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level.

	(1) Low-Func.	(2) S.C.H.	(3) Either	(4) Low-Func.	(5) S.C.H.	(6) Either
Excess Rehab	0.00320***	0.00612***	0.00776***	0.00136**	0.00395***	0.00474***
	(4.22)	(5.85)	(8.86)	(2.23)	(4.38)	(5.63)
Quarter-Year FE	Yes	Yes	Yes	No	No	No
Patient Gender	No	No	No	Yes	Yes	Yes
Age Bucket	No	No	No	Yes	Yes	Yes
Patient Race	No	No	No	Yes	Yes	Yes
County x Quarter FE	No	No	No	Yes	Yes	Yes
Diagnosis x Hospitalization Length	No	No	No	Yes	Yes	Yes
Observations	39,416	39,416	39,416	36,691	36,691	36691
Adjusted R^2	0.005	0.008	0.010	0.051	0.104	0.092

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.VII. Excess Rehab and CMS Outcomes

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with CMS payment denials and designations by estimating the following OLS regression:

$$y_{jt} = \alpha + \beta ExcessRehab_j + FixedEffects + \epsilon_{jt}$$

where y_{jt} is a facility-level measure of either payment denial (column 1) or watchlist status (columns 2-3). Data comes from Public Use Files and is reported on an annual basis from 2016-2022 for payment denials and Special Focus status. The Special Focus Candidate variable is only available for years 2019-2022. Payment denials is the count of payment denials by Medicare for invalid claims. Special Focus status (column 2) is a designation given to facilities of concern by CMS for facilities that are dramatically and persistently under performing. Finally, Special Focus Candidate (column 3) includes not only facilities classified as a Special Focus Facility, but also facilities whose performance on staffing, health inspections, and quality measures places them at increased risk of being included on the list. Robust standard errors are clustered at the SNF system level and t statistics are presented in parentheses.

	(1) Payment Denials	(2) Special Focus	(3) Special Focus Candidate
Excess Rehab	0.00441***	0.000583***	0.00286***
	(4.01)	(3.24)	(4.23)
County FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Observations	54645	53646	31505
Adjusted R^2	0.152	0.038	0.084

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.VIII. Difference-in-Differences around PDPM Adoption

In this table, we explore the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with billing intensity under PDPM. We estimate a difference-in-differences regression of the form:

$$y_{ijt} = \alpha + \beta Opportunistic_j \times Post + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a patient condition that qualifies for additional compensation under PDPM, but not under RUG-IV. $Opportunistic_j$ is an indicator equal to one if a facility belongs to an SNF system which was in the highest tercile of excess rehab during RUG-IV according to Equation 1. *Acute* is an indicator variable equal to one if patient i's primary diagnosis belongs to the Acute Neurologic clinical category, SLP is an indicator variable equal to one if at least one SLP-related comorbidity is included among patient i's diagnoses codes, and NTA is a weighted sum of NTA-related comorbidities. *Post* is an indicator variable for admissions after PDPM becomes effective in October 2019. To control for time-invariant differences in propensity across facilities, we include an individual facility fixed effect in all specifications. Robust standard errors are clustered at the SNF system level and t statistics are reported in parentheses.

	(1) Acute	(2) SLP	(3) NTA	(4) Acute	(5) SLP	(6) NTA
Opportunistic × Post	0.0580***	0.0217***	0.0655***	0.0459***	0.0134***	0.0553***
	(6.54)	(3.86)	(3.30)	(6.21)	(3.78)	(3.91)
Patient Gender	No	No	No	Yes	Yes	Yes
Age Bucket	No	No	No	Yes	Yes	Yes
Patient Race	No	No	No	Yes	Yes	Yes
County x Quarter FE	No	No	No	Yes	Yes	Yes
Diagnosis x Hospitalization Length	No	No	No	Yes	Yes	Yes
Facility FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	No	No	No
Observations	8,939,993	8,939,993	8,939,993	8,929,613	8,929,613	8929613
Adjusted R^2	0.042	0.029	0.053	0.265	0.138	0.183

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.IX. Billing Following Acquisition: Stacked Difference-in-Differences

This table investigates the incidence of billing intensity around acquisition by opportunistic SNF systems by estimating the following stacked cohort difference-in-difference regression:

$$Y_{ijt} = \alpha + \sum_{t=1}^{T} \beta_t Period_t \times AcquiredOpportunstic_j + \Gamma_{jc} + \delta_{tc} + \epsilon$$

where Y_{ijt} is the outcome variable of interest and is either individual billing categories (columns 1-5) or coding intensity (column 6). $AcquiredOpportunistic_j$ is an indicator variable equal to one if a facility was acquired by an opportunistic SNF system, defined as systems in the highest tercile of excess rehab during RUG-IV according to Equation 1. We consider a window of eight quarters before and after acquisition. The quarter before acquisition is omitted from the specification and is the reference group. All specifications include a facility × cohort and quarter-year × cohort fixed effect. Robust standard errors are clustered at the facility level and t statistics are reported in parentheses.

	(1) Low Func.	(2) S.C.H.	(3) Depression	(4) SLP High	(5) Diet	(6) Code Intens.
Acq × Pre8	0.00132	-0.000560	0.00623	-0.000147	-0.0109	-0.00402
	(0.13)	(-0.04)	(0.64)	(-0.02)	(-1.35)	(-0.14)
Acq × Pre7	0.00829	-0.00336	-0.00603	-0.0134*	-0.0118*	-0.0262
	(0.93)	(-0.21)	(-0.59)	(-1.68)	(-1.64)	(-0.84)
Acq × Pre6	0.00183	0.0149	-0.00227	-0.00738	-0.00342	0.00364
	(0.23)	(1.12)	(-0.25)	(-1.02)	(-0.50)	(0.14)
Acq × Pre5	-0.00492	-0.00318	-0.0162*	0.00354	0.00100	-0.0198
	(-0.57)	(-0.24)	(-1.78)	(0.47)	(0.15)	(-0.71)
Acq × Pre4	-0.00500	-0.00528	-0.0123	0.00362	0.00137	-0.0176
	(-0.61)	(-0.43)	(-1.37)	(0.52)	(0.24)	(-0.67)
Acq × Pre3	0.000501	0.00631	-0.0179**	-0.0123**	-0.00415	-0.0276
	(0.07)	(0.68)	(-2.37)	(-2.08)	(-0.77)	(-1.38)
Acq × Pre2	-0.000541	-0.00792	-0.00921	-0.0117**	-0.00116	-0.0305*
	(-0.09)	(-0.91)	(-1.43)	(-2.12)	(-0.24)	(-1.70)
Acq × Post1	0.00868	0.0231**	0.00654	0.0206***	0.000495	0.0594***
	(1.38)	(2.08)	(0.95)	(3.15)	(0.09)	(2.77)
Acq × Post2	0.00673	0.0684***	0.0415***	0.0259***	0.0197***	0.162***
	(0.97)	(4.65)	(3.64)	(3.26)	(2.96)	(5.20)
Acq × Post3	-0.000501	0.0702***	0.0493***	0.0289***	0.0170**	0.165***
	(-0.06)	(4.67)	(3.68)	(3.34)	(2.39)	(4.84)
Acq × Post4	0.00910	0.0850***	0.0589***	0.0377***	0.0193**	0.210***
	(0.98)	(5.21)	(3.32)	(3.98)	(2.30)	(5.45)
Acq × Post5	0.0141	0.0968***	0.0713***	0.0386***	0.0245***	0.245***
	(1.32)	(5.86)	(3.99)	(4.05)	(2.90)	(6.27)
Acq × Post6	0.00337	0.0927***	0.0688***	0.0353***	0.0149	0.215***
	(0.29)	(5.34)	(3.94)	(3.47)	(1.61)	(5.23)
Acq × Post7	0.00813	0.105***	0.0663***	0.0450***	0.00751	0.232***
	(0.67)	(5.76)	(3.16)	(4.55)	(0.87)	(5.27)
Acq × Post8	-0.00259	0.131***	0.0412**	0.0249*	0.00871	0.204***
	(-0.24)	(5.27)	(1.98)	(1.90)	(0.87)	(3.91)
Facility × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Quarter × Cohort	Yes	Yes	Yes	Yes	Yes	Yes
Observations	72,620,494	72,620,494	72,620,494	72,620,494	72,620,494	72,620,494
Adjusted R^2	0.057	0.143	0.243	0.061	0.077	0.169

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.X. Excess Rehab and Patient Reviews

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with assessments of quality from patient reviews by estimating a regression of the form:

$$y_{ji} = \alpha + \beta ExcessRehab_j + FixedEffects + \epsilon_{jt}$$

where y_{ji} is a measure of perceived care quality. Abuse (columns 1, 4) is an indicator variable equal to one if our Support Vector Machine (SVM) algorithm identifies a review as being indicative of abuse with at least 90% probability. Review stars (columns 2, 5) range from one (worst) to five (best). Text sentiment (columns 3, 6) is an additional measure of patient satisfaction and ranges from negative one (most negative) to one (most positive). Columns 1-3 report regressions at the individual review level while columns 4-6 report regressions at the SNF system level. Standard errors for review-level specifications are clustered at the SNF system level.

	(1) Abuse	(2) Stars	(3) Sentiment	(4) Abuse	(5) Stars	(6) Sentiment
Excess Rehab	0.00522***	-0.0249***	-0.00313***	0.00489***	-0.0243***	-0.00261***
	(5.15)	(-4.81)	(-4.92)	(7.07)	(-6.03)	(-4.51)
Observations	39,335	37,219	37,219	525	517	517
Adjusted R^2	0.004	0.005	0.004	0.085	0.064	0.036

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XI. Excess Rehab and Patient Health Outcomes

In this table, we examine the relationship of SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with patient health outcomes. We estimate an OLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a patient health outcome for patient i admitted to facility j at time t. Pressure ulcer and UTI development are computed from subsequent hospital stays using the Inpatient Limited Data Set. Only patients admitted with such conditions within two days of leaving the skilled nursing facility are considered in this measure. *Rehospitalization* is an indicator for whether a patient was subsequently hospitalized in the 30 days following discharge. *Mortality* is an indicator for whether a patient dies within 90 days of being discharged from a skilled nursing facility. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length refers to the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level.

	(1) Pressure Ulcer	(2) UTI	(3) Rehospitalized	(4) Mortality
Excess Rehab	0.000212***	0.000557***	0.00239***	0.00154***
	(7.91)	(12.39)	(11.75)	(9.59)
Patient Gender	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Length	Yes	Yes	Yes	Yes
Observations	6,194,050	6,194,050	6,194,050	6,194,050
Adjusted R^2	0.010	0.010	0.054	0.077

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XII. Excess Rehab and Facility Health Inspections

In this table, we examine the relationship between SNF system-level excess rehab during the Resource Utilization Group IV (RUG-IV) era (January 1, 2016-September 30, 2019) with outcomes from unannounced health inspections by estimating the following OLS regression:

$$y_{jt} = \alpha + \beta ExcessRehab_j + FixedEffects + \epsilon_{jt}$$

where y_{jt} is a facility-level measure of health inspection. Data on inspection outcomes comes from Public Use Files and is reported on an annual basis from 2016-2022. The outcome variables vary by column. Inspection rating ranges from one star (worst) to five stars (best). Weighted deficiencies is the weighted sum of deficiencies found during health inspections. Weights come from CMS and more serious infractions are given heavier weights. Complaints denotes the amount of consumer complaints that are validated by state agencies during health inspections. Fine count is the total number of fines received by an individual SNF facility. Finally, Fine $ is the total amount of fines received in USD. Robust standard errors are clustered at the SNF system level.

	(1) Inspection Rating	(2) Weighted Defic.	(3) Complaints	(4) Fine Count	(5) Fine $
Excess Rehab	-0.0398***	1.873***	0.237***	0.0205***	863.0***
	(-8.89)	(7.79)	(6.38)	(5.74)	(6.07)
County FE	Yes	Yes	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes	Yes	Yes
Observations	53,969	54,157	54,645	54,645	54,645
Adjusted R^2	0.232	0.250	0.273	0.219	0.123

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XIII. Instrumental Variables-First Stage (90% Cutoff)

In this table, we present results for the first stage of the instrumental variables specification. We instrument for excess rehab faced by a patient by utilizing variation in occupancy levels of competing facilities. The instrument, $PredictedExcessRehab$ comes from a weighted average of excess rehab within a Hospital Service Area. Weights derive from the occupancy levels of competing facilities according to Equation 4, but the cutoff for $Constrained$ is 0.90. We then estimate the first-stage with a regression of the form:

$$ExcessRehab_{ijt} = \alpha + \beta PredictedExcessRehab_{jt} + \theta X_i + FixedEffects + \epsilon$$

where $ExcessRehab_{ijt}$ is the excess rehab for facility j selected by patient i at time t. To control for time-invariant variation in excess rehab levels due to geographic concentration of SNF systems, we include a Hospital Service Area fixed effect. Robust standard errors are clustered at the SNF system level and t statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Excess Rehab	0.398***	0.398***	0.376***	0.400***	0.400***	0.411***
	(9.50)	(9.50)	(11.27)	(9.74)	(9.75)	(10.55)
Quarter-Year FE	Yes	No	No	Yes	No	No
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis FE	Yes	No	No	Yes	No	No
County x Quarter FE	No	No	Yes	No	No	Yes
Diagnosis x Hospitalization Stay	No	Yes	Yes	No	Yes	Yes
HSA FE	No	No	No	Yes	Yes	Yes
Observations	1,618,466	1,613,870	1,609,905	1,618,466	1,613,870	1,609,904
Adjusted R^2	0.402	0.402	0.606	0.758	0.757	0.770

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XIV. Instrumental Variables-First Stage (95% Cutoff)

In this table, we present results for the first stage of the instrumental variables specification. We instrument for excess rehab faced by a patient by utilizing variation in occupancy levels of competing facilities. The instrument, $PredictedExcessRehab$ comes from a weighted average of excess rehab within a Hospital Service Area. Weights derive from the occupancy levels of competing facilities according to Equation 4, but the cutoff for $Constrained$ is 0.95. We then estimate the first-stage with a regression of the form:

$$ExcessRehab_{ijt} = \alpha + \beta PredictedExcessRehab_{jt} + \theta X_i + FixedEffects + \epsilon$$

where $ExcessRehab_{ijt}$ is the excess rehab for facility j selected by patient i at time t. To control for time-invariant variation in excess rehab levels due to geographic concentration of SNF systems, we include a Hospital Service Area fixed effect. Robust standard errors are clustered at the SNF system level and t statistics are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Predicted Excess Rehab	0.437***	0.437***	0.397***	0.430***	0.430***	0.428***
	(10.33)	(10.34)	(10.71)	(10.28)	(10.30)	(10.30)
Quarter-Year FE	Yes	No	No	Yes	No	No
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis FE	Yes	No	No	Yes	No	No
County x Quarter FE	No	No	Yes	No	No	Yes
Diagnosis x Hospitalization Stay	No	Yes	Yes	No	Yes	Yes
HSA FE	No	No	No	Yes	Yes	Yes
Observations	1,618,466	1,613,870	1,609,905	1,618,466	1,613,870	1609904
Adjusted R^2	0.419	0.419	0.612	0.768	0.768	0.775

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XV. Instrumental Variables-Second Stage (90% Cutoff)

In this table we examine the effect of excess rehab billing on PDPM billing intensity. We estimate a 2SLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a measure of billing intensity for patient i at facility j during quarter t and is an indicator for a patient being classified as either Low Function, Special Care High, Depression, SLP High or Dietary Restriction. We instrument for $ExcessRehab_j$ using $PredictedExcessRehab$ from Equation 5, except that the cutoff for $Constrained$ is 90%. Low Function, Special Care High, and Depression are classifications that impact the Nursing component of PDPM case-mix and increase reimbursement. SLP High and Dietary Restriction classification increase PDPM reimbursements for the SLP component (as shown in Exhibits 2 and 1). Patient controls include gender, age (in five-year increments), and race. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length refers to the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level.

	(1) Low Func.	(2) S.C.H.	(3) Depression	(4) SLP High	(5) Diet	(6) Code Intens.
Excess Rehab	0.00274***	0.00744***	0.00801***	0.00595***	0.00402***	0.0282***
	(3.68)	(5.71)	(5.88)	(14.34)	(6.17)	(8.75)
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Stay	Yes	Yes	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,609,904	1,609,904	1,609,904	1,609,904	1,609,904	1,609,904

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.XVI. Instrumental Variables-Second Stage (95% Cutoff)

In this table we examine the effect of excess rehab billing on PDPM billing intensity. We estimate a 2SLS regression of the form:

$$y_{ijt} = \alpha + \beta ExcessRehab_j + \theta X_i + FixedEffects + \epsilon_{ijt}$$

where y_{ijt} is a measure of billing intensity for patient i at facility j during quarter t and is an indicator for a patient being classified as either Low Function, Special Care High, Depression, SLP High or Dietary Restriction. We instrument for $ExcessRehab_j$ using $PredictedExcessRehab$ from Equation 5, except that the cutoff for $Constrained$ is 95%. Low Function, Special Care High, and Depression are classifications that impact the Nursing component of PDPM case-mix and increase reimbursement. SLP High and Dietary Restriction are classifications that increase PDPM reimbursements for the SLP component (as shown in Exhibits 2 and 1). Patient controls include gender, age (in five-year increments), and race. Fixed effects are as indicated at the bottom of each column. Patient diagnosis comes from the referring hospital and is at the CCSR-level. Hospitalization length refers to the number of days for which a patient was hospitalized at an inpatient facility prior to beginning their SNF stay. Robust standard errors are clustered at the SNF system level.

	(1) Low Func.	(2) S.C.H.	(3) Depression	(4) SLP High	(5) Diet	(6) Code Intens.
Excess Rehab	0.00259***	0.00745***	0.00777***	0.00597***	0.00416***	0.0279***
	(3.65)	(5.72)	(6.04)	(14.01)	(6.62)	(8.81)
Patient Gender	Yes	Yes	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Stay	Yes	Yes	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,609,904	1,609,904	1,609,904	1,609,904	1,609,904	1,609,904

t statistics in parentheses
* p<0.10, ** p<0.05, *** p<0.010

Table IA.XVII. Excess Rehab and Patient Health Outcomes (IV 90% Cutoff)

This table presents IV results for regressions of patient health outcomes on SNF system excess rehab. *ExcessRehab* is instrumented using *PredictedExcessRehab* as defined in Table IA.III, except that the cutoff for *Constrained* is 90%. Fixed effects are as indicated at the bottom of each column. Robust standard errors are clustered at the SNF system level.

	(1) Pressure Ulcer	(2) UTI	(3) Rehospitalized	(4) Mortality
Excess Rehab	0.000193***	0.000546***	0.00252***	0.00228***
	(3.19)	(7.40)	(6.70)	(7.95)
Patient Gender	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Stay	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes
Observations	1,609,904	1,609,904	1,609,904	1,609,904

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010

Table IA.XVIII. Excess Rehab and Patient Health Outcomes (IV 95% Cutoff)

This table presents IV results for regressions of patient health outcomes on SNF System excess rehab. $ExcessRehab$ is instrumented using $PredictedExcessRehab$ as defined in Table IA.III, except that the cutoff for $Constrained$ is 95%. Fixed effects are as indicated at the bottom of each column. Robust standard errors are clustered at the SNF system level.

	(1) Pressure Ulcer	(2) UTI	(3) Rehospitalized	(4) Mortality
Excess Rehab	0.000206***	0.000554***	0.00263***	0.00224***
	(3.55)	(7.47)	(7.38)	(7.67)
Patient Gender	Yes	Yes	Yes	Yes
Age Bucket	Yes	Yes	Yes	Yes
Patient Race	Yes	Yes	Yes	Yes
County x Quarter FE	Yes	Yes	Yes	Yes
Diagnosis x Hospitalization Stay	Yes	Yes	Yes	Yes
HSA FE	Yes	Yes	Yes	Yes
Observations	1,609,904	1,609,904	1,609,904	1,609,904

t statistics in parentheses

* p<0.10, ** p<0.05, *** p<0.010