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ABSTRACT

The landscape of the U.S. healthcare industry is changing dramatically as healthcare providers expand both within and across markets. While federal antitrust agencies have mounted several challenges to same-market combinations, they have not challenged any non-horizontal affiliations – including vertical integration of providers along the value chain of production. The Clayton Act prohibits combinations that "substantially lessen" competition; few empirical studies have focused on whether this is the source of harm from vertical combinations. We examine whether hospitals that are vertically integrated with skilled nursing facilities (SNFs) lessen competition among SNFs by foreclosing rival SNFs from access to the most lucrative referrals. Exploiting a plausibly exogenous shock to Medicare reimbursement for SNFs, we find that a 1 percent increase in a patient's expected profitability to a SNF increases the probability that a hospital self-refers that patient (i.e., to a co-owned SNF) by 2.5 percent. We find no evidence that increased self-referrals improve patient outcomes or change post-discharge Medicare spending. Additional analyses show that when integrated SNFs are divested by their parent hospitals, independent rivals are less likely to exit. Together, the results suggest vertical integration in this setting may reduce downstream competition without offsetting benefits to patients or payers.

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A data appendix is available at http://www.nber.org/data-appendix/w28305

1. Introduction

Over the past few decades, ownership links across health care organizations have multiplied, yielding increasingly complex systems comprised of formerly distinct provider organizations. The number of mergers and acquisitions among hospitals alone totaled 1,412 over the period 1998-2015.[1] The increasing size and geographic footprint of hospital systems has coincided with a swift increase in hospital acquisitions of physician practices, as well as a range of other provider types, including urgent care centers and ambulatory service centers. In addition, a growing set of hospitals and post-acute care providers have common investors (Fowler et al., 2017).

A sizeable empirical literature explores the impacts of horizontal integration of direct competitors in healthcare settings, concluding that it typically results in higher prices and spending for downstream consumers, without commensurate quality improvements. Antitrust enforcers regularly challenge these transactions, using the principles outlined in the *Horizontal Merger Guidelines* issued jointly by the Federal Trade Commission and the Antitrust Division of the Department of Justice.

The literature on vertical integration of providers at different stages of the value chain primarily considers hospital-physician affiliations (e.g., Capps et al., 2018; Neprash et al., 2015; Baker et al., 2014; Robinson and Miller, 2014; McWilliams et al., 2018).[2] These studies collectively show that hospital-physician affiliations tend to harm consumers through higher prices and spending, and no observable quality improvements. To date, however, neither federal enforcement agency has challenged a healthcare provider merger on vertical grounds, causing industry participants and observers to assume that these transactions are unlikely to receive scrutiny.[3] In June 2020, the FTC and DOJ issued the first joint *Vertical Merger Guidelines*,

[1] American Hospital Association Trendwatch Chartbook 2016. https://www.aha.org/system/files/2018-01/2016-chartbook.pdf.

[2] Two studies suggest integration of medical and pharmaceutical benefits is an exception. Lavetti and Simon (2018) and Starc and Town (2019) find evidence that Medicare Advantage plans combining medical and drug coverage offer more generous drug coverage, particularly for "offset drugs" that treat chronic conditions and whose utilization lowers medical spending.

[3] An exception is the recent CVS-Aetna merger, which included vertical elements as CVS owned drugstores and retail clinics that supplied services to enrollees in Aetna's various health plans. There were numerous state and federal hearings about the transaction, which was proposed in 2017 and ultimately cleared in 2019. However, the primary cause of delay was a highly unusual and protracted battle between DOJ and the federal judge overseeing the

signaling potentially heightened attention to these transactions going forward. The guidelines discuss various mechanisms for anticompetitive effects of vertical transactions; they also discuss pro-competitive "efficiencies" that enforcement agencies may consider as offsetting benefits if they are passed through to consumers. As in the *Horizontal Merger Guidelines*, the *Vertical Merger Guidelines* emphasize that the Clayton Act proscribes acquisitions that "substantially lessen" competition. The phrasing suggests post-merger consumer harm (e.g., increases in spending following hospital acquisition of an outpatient clinic) alone may be viewed by the federal agencies as insufficient grounds for a merger challenge.

Post-merger increases in prices and spending could arise for a number of reasons apart from the lessening of competition set out in the Clayton Act. The merging parties could have different degrees of risk tolerance or bargaining ability, yielding higher post-merger negotiated prices (Lewis and Pflum, 2017). "Mechanical" price changes may occur as a result of payer reimbursement schedules, which often have site of service differentials (Dranove and Ody, 2019; Song et al., 2015).[4] We examine one of the primary mechanisms for vertical affiliations to lessen competition, and therefore to form the basis for a challenge under the Clayton Act: foreclosure of inputs to a rival in a downstream market.

In the context of hospital-physician mergers, a hospital might foreclose rival hospitals from access to patients by requiring or pressuring newly owned practices to refer exclusively to the parent hospital(s).[5] Relatedly, newly owned providers might refer the most profitable patients to the parent organization and/or send the least profitable patients to rivals, potentially leading rivals to increase prices, reduce quality, or cease operations in response. The exit or contraction of rivals, as well as the potentially diminished threat of entrants, will also reduce competitive pressures on incumbents.

settlement agreement between DOJ and the merging parties ("CVS-Aetna Merger Cleared After Unprecedented Court Battle," B. Koenig, *Law360*, September 4, 2019.)

[4] Arguably, persistence of such "mechanical" price changes (i.e., inability of an insurer to renegotiate the pricing terms) can arguably be linked to a lessening of competition.

[5] For example, St. Alphonsus Medical Center filed a lawsuit in 2014 against its competitor St. Luke's Health System, alleging that St. Luke's acquisition of an outpatient physician practice could foreclose St. Alphonsus from competing against St. Luke's in inpatient services by depriving St. Alphonsus of patient referrals. The lawsuit was merged with a lawsuit by the Federal Trade Commission, which alleged harm on horizontal grounds, specifically that the combination of St. Luke's pre-existing physician practices and the target would enable the merged entity to raise costs for healthcare services provided by primary care physicians in the area in and around Nampa, Idaho. The judge sided with the FTC and blocked the transaction; he declined to rule on the vertical claim alleged by St. Alphonsus.

In this study, we examine whether hospitals that own skilled nursing facilities (SNFs) are likelier to self-refer more profitable Medicare patients, and whether any increase in self-referrals leads to changes in patient outcomes or total spending. In addition to serving as a setting for exploring the competitive effects of vertical integration, the relationship between hospitals and SNFs is of significant interest given the role of post-acute care (i.e., care following an inpatient stay) in the U.S. SNF and post-acute home health services consistently accounted for around 15 percent of fee-for-service Medicare spending from 2007 to 2018. Roughly 20 percent of Medicare patients are discharged to a SNF following an inpatient stay, and SNF spending accounts for roughly half of Medicare's spending on post-acute care.[6,7]

Using detailed claims data for all "traditional" (fee-for-service) Medicare enrollees admitted to general acute-care hospitals between 2008-2012, we explore whether vertically integrated hospital-SNFs responded to a 2010 shock to SNF reimbursement by increasing (decreasing) self-referral of patients who became relatively more (less) profitable.[8] SNFs owned by critical-access hospitals (CAHs) were not impacted, as they are reimbursed under a different (cost-plus) arrangement. Thus, vertically-integrated CAHs form a natural control group for vertically-integrated general acute care (GAC) hospitals. Among the vertically-integrated GAC hospitals, we find clear evidence of post-shock increases in the self-referral rate among patients that became more profitable. There is no change in the self-referral rate for similar patients admitted to vertically-integrated CAHs.

We then examine the impact of self-referral on patient-level spending and health outcomes. For this analysis, the control group consists of patients admitted to GAC hospitals that did not own a SNF. While among these hospitals the propensity for self-referral is zero before and after the reform, SNFs receiving patients from such hospitals were still impacted by the reimbursement changes, allowing for any impact of these changes (apart from the effect on self-referral) to be common to the treatment and control groups. We do not find evidence that the increase in self-referrals among vertically-integrated GAC hospitals improved clinical outcomes

[6] Source for SNF and home health agency share of Medicare spending is from the MedPAC "Health Care Spending and the Medicare Program" databooks from 2018 and 2019.
[7] In 2017, self-care at home (45 percent) was the most common discharge destination, followed by SNF care (21 percent), home health care (18 percent), and inpatient rehabilitation facility care (4 percent). Three percent of patients died in the hospital (MedPAC 2019).
[8] As discussed below, patients that became more profitable include those with degenerative nurse disease, psychosis, and stroke. Patients that became less profitable include those with joint replacement, heart attacks, and pneumonia.

(specifically, 90-day mortality and readmission rates), nor does it appear to have impacted costs of care in the 90 days following discharge.

To evaluate whether vertically integrated SNFs contribute to the exit of independent rivals, we conduct a separate event study analysis of acquisitions and divestitures of SNFs by hospitals, over the period 2010-2017. We find independent SNFs are less (more) likely to exit when a hospital divests (acquires) a rival.

Put together, the results show vertically-integrated hospital-SNF entities steer more profitable patients toward their own SNFs, which is likely to weaken rivals and therefore diminish competition for patients. On average, SNFs earned an additional $175 per self-referral induced by this reform, boosting profit margins on these referrals by 1 percentage point, a substantial increase relative to baseline profit margins during this period of around 2 percent. We find no evidence that self-referrals improve patient outcomes or lower costs, although because of imprecision in the estimates, we are unable to rule out meaningful changes. We also find that independent SNFs are less likely to exit after integrated hospitals divest a rival SNF (i.e. dis-integrate). These findings run counter to claims that vertical integration of acute and post-acute providers yields quality improvements or cost reductions (i.e., "efficiencies" in antitrust vernacular) and suggest integration may actually harm consumers by inducing the exit of independent rivals. These effects could theoretically be mitigated by payment mechanisms introduced since our study period, e.g. shared-savings programs that reward provider groups for reducing total costs of care while maintaining or improving quality. However, research suggests most savings have occurred outside of vertically integrated organizations (e.g., McWilliams et al. 2018).

Our study complements and extends prior literature on self-referrals, SNF care, and vertical integration of healthcare providers. In particular, the practice of self-referring the most profitable patients is documented in Nakamura et al. (2007) and Barro et al. (2006). Nakamura et al. find "feeder" or community hospitals acquired by large tertiary care hospitals increased privately-insured referrals and decreased Medicaid referrals to their new tertiary owner. Barro et al. find evidence of "cherry picking" by for-profit, physician-owned cardiac specialty hospitals, i.e. physicians refer healthier patients more suitable for lucrative surgical procedures to their co-owned facilities. We show this practice arises in the setting of acute and post-acute provider affiliations, and extend the analysis by considering the dynamic effects on market structure.

Our work also complements prior studies on hospital-SNF referrals. Doyle et al. (2017) find that patients treated at hospitals with higher proclivities to discharge to SNFs experience higher post-discharge spending and mortality.[9] Konetzka et al. (2018) examine the impact of vertical integration between hospitals and SNFs on patient-level outcomes using the distance between a patient's nearest SNF-integrated and non-integrated hospital as an instrument for admission to an integrated facility.[10] They find lower readmission rates but higher post-discharge spending for patients self-referred to a SNF. The study design jointly tests the effect of the hospital-SNF pair on patient outcomes. In contrast, we study the impact of receiving treatment in a vertically integrated SNF; our strategy eliminates treatment effects associated with differences among the hospitals that elect to become vertically integrated.

The remainder of this article proceeds as follows. Section 2 provides background on the SNF reimbursement system and hospital-SNF integration. Section 3 describes the data and reimbursement change that is central to our identification strategy. Section 4 introduces our empirical models and presents our principal analyses. Section 5 explores heterogeneity and robustness checks for our results. Section 6 concludes.

2. Background

2.1 Vertical Integration of Healthcare Providers

Vertical integration refers to a combination of firms that operate at different points along the vertical chain of production, such as car assemblers and parts manufacturers, or health insurers and ambulatory surgery centers. The potential benefits of vertical integration include improved alignment of objectives across the two firms (which may be hard to achieve through contracting), a greater willingness to undertake value-creating relationship-specific investments (as the risk of hold-up and the transactions cost associated with contracting are eliminated), and a reduction in prices due to the elimination of "double marginalization."[11] If realized, vertically

[9] Doyle et al. (2017) note there are multiple potential explanations for their findings, including the possibility that patients receive worse care from these SNFs than they would from other post-acute care providers, or that these hospitals have worse outcomes for other reasons.
[10] The specification also includes hospital-SNF pair fixed effects, so as to isolate "within-provider effects of changing integration status on patient outcomes." Thus, the effect of vertical integration on a patient is identified from variation in the outcomes for patients who are exogenously more likely to be admitted to an integrated pair, where that likelihood varies due to patient location as well as to changes in provider integration.
[11] For a comprehensive discussion of integration motives and potential efficiencies, see Chapter 7 of Economics of Strategy (Besanko et al 2017) and Post et al. (2018).

integrated firms may find it optimal to "pass through" some of these benefits to downstream consumers. On the flip side, potential downsides of vertical integration include intraorganizational diseconomies of scope, diminished performance incentives because the upstream firm has a guaranteed purchaser of its input, and potentially higher prices arising from the incentive for an integrated firm to weaken or induce the exit of rivals by reducing access or raising the price of the input.[12]

In the context of vertical mergers among health service providers, one specific concern is the risk of inefficient "self-referrals" to co-owned providers. These referrals may be for care that is unnecessary (and potentially harmful, beyond being costly), as shown in Afendulis and Kessler (2007). Providers might also refer patients to co-owned providers who are higher-cost or lower-quality than alternative providers, as found in Baker et al. (2016). Relatedly, changes in ownership structure can enable higher prices for the same services – literally overnight - as occurs when formerly independent physician practices are acquired by hospitals and their services are billed by the hospital outpatient department, which has higher reimbursement rates (Koch et al. 2017; Capps et al. 2018). Vertical integration may also increase providers' market power and bargaining leverage over insurers if consumers of health insurance consider the different providers to be substitutes rather than complements in the insurers' network of providers (Dafny et al., 2019; Easterbrook et al. 2019).[13] Finally, vertically integrated providers could raise rivals' costs or foreclose them from access to a critical input – in this case, profitable patients.

As previously noted, the literature on vertical provider mergers to date is not sanguine with respect to consumer benefits. Most of this literature focuses on hospital-physician integration. Several studies find that hospital-physician integration raises healthcare prices and spending (e.g., Baker et al., 2014; Capps et al., 2018; Koch et al. 2017; McWilliams, et al., 2018; Neprash et al., 2015; Robinson and Miller, 2014). Recent studies that examine the effect of vertical provider integration on quality generally do not find evidence of improved clinical outcomes (e.g., Ho et al. 2019; Koch et al. 2018), although some find evidence of process and

[12] The downstream component of the integrated firm also has a reduced incentive to buy from upstream competitors.
[13] While the direction of the effect on pricing differs in Easterbrook et al. (2019) and Dafny et al. (2019), the change in pricing in both papers results from the merging partner internalizing the effect of its contracting decision on the profits of the merging partner. If the providers are complements, this will lead to a decrease in prices through the elimination of double marginalization. If the providers are substitutes, this will lead to an increase in prices.

screening improvements (e.g. Carlin et al. 2015 and Bishop et al. 2016).[14] Konetzka et al. (2018) find Medicare patients receiving both inpatient and SNF care in vertically integrated hospital-SNF entities experience lower readmission rates but higher 60-day post-discharge spending; our study is complementary in that we focus on the likelihood of self-referral by integrated hospitals and its impacts on patient outcomes and rival exit decisions.

2.2 SNFs and the 2010 Change in Medicare Reimbursement of SNFs

SNFs provide patients with short-term rehabilitative and nursing services following inpatient stays. Nearly three-quarters of SNFs are for-profit, and their total number has been relatively steady with 15,090 facilities in 2017 (down slightly from 15,178 in 2006). Medicare covered 2.2 million stays in SNFs in 2017, with total payments of $25.9 billion. Because Medicare's SNF benefit is limited to short-term rehabilitation, whereas Medicaid covers long-term care, Medicare's share of revenues is smaller (19 percent in 2017 vs. around 50 percent for Medicaid). At the same time, treating Medicare patients is much more profitable, so the program may have a disproportionate effect on the conduct of SNFs and their parent organizations.[15]

Between 1998 and 2019, Medicare reimbursed for most SNF care at a prospective daily rate.[16] The rate varies based on three factors: whether the SNF is in an urban or rural area, local wages, and the patient's Resource Utilization Group (or RUG). At the time of admission and periodically afterwards, the SNF assesses each patient using a standardized questionnaire via the Minimum Data Set (MDS).[17] The MDS questionnaire addresses the degree to which the patient can perform a number of activities (e.g. independently use the toilet or get dressed) and whether the patient needs specialized services (e.g. dialysis or tracheostomy care). Based on questionnaire responses, the patient is assigned a RUG code; patients with similar therapy and

[14]As our focus is integration among providers, we do not summarize the lengthy literature regarding integration of providers and insurers, nor the recent literature pertaining to integration of medical and pharmaceutical benefits. For the former, see Goldsmith et al. (2015); for the latter, see Starc and Town (2019).
[15] Sources for all reported SNF industry statistics are the annual MedPAC "Health Care Spending and the Medicare Program" databooks from 2016, 2018, and 2019. The March 2019 MedPAC Report to Congress reports that the average total margin for SNFs in 2017 was 0.5 percent, and the average non-Medicare margin was -2.4 percent.
[16] In October 2019, the Centers for Medicare and Medicaid services (CMS) adopted the Patient-Driven Payment Model, which discontinued the use of Resource Utilization Groups in setting payments.
[17] All patients admitted to a SNF receive a "5-day assessment," which determines reimbursement for days 1 through 14 of the patient stay; SNFs typically complete these within 5 days of admission. If a stay progresses beyond 14 days, the SNF will perform a new assessment at specific intervals (14, 30, and 90 days), and that assessment will determine reimbursements until the next assessment date.

nursing assistance needs are assigned to the same RUG code. Upcoding patients into more remunerative RUG codes is a well-documented practice (Bowblis and Brunt, 2014; Levinson, 2010). Given our interest is in how patient profitability impacts self-referrals and quality of care, our analysis isolates changes in profitability not related to upcoding.

We isolate changes in profitability that resulted from the change in the RUG classification system effective October 2010, which at the time represented the largest revision to the reimbursement system since the Centers for Medicare and Medicaid Services (CMS) introduced the SNF Prospective Payment System in 1998. The transition from RUG-III to RUG-IV (the "RUG update") implemented three key changes, designed to better match reimbursement with care expenses and needs.[18,19] First, CMS altered the MDS questionnaire used to assign patients to a RUG. The new assessment was backward-compatible but not forward-compatible.[20] Second, CMS updated its estimates of the quantities of therapy and nursing services needed for each RUG code, as well as the associated RUG reimbursement rates. Third, CMS increased the number of RUGs from 53 to 66. These changes in reimbursement rates generate quasi-experimental variation in prices paid to SNFs following the 2010 RUG update (hereafter, the "price shock").

The RUG update inadvertently led to increases in aggregate SNF reimbursements in FY2011. In response, CMS adjusted rates downward for FY2012, but as we show below, the update-induced *relative* changes in prices persisted.[21] The descriptive statistics below reveal that on net, the shock improved the relative profitability of Black and Medicaid-eligible patients, as well as patients diagnosed with a degenerative nerve disease, psychosis, or stroke, and decreased the relative profitability of patients hospitalized for joint replacement, heart attack, or pneumonia.

[18] "Medicare Program; Prospective Payment System and Consolidated for Skilled Nursing Facilities for FY 2010; Minimum Data Set, Version 3.0 for Skilled Nursing Facilities and Medicaid Nursing Facilities." 74 Fed. Reg. § 40287 (final rule August 11, 2009) (to be codified at 42 C.F.R. pt. 483).
[19] There were no significant changes to the RUG system in the five years preceding this transition from RUG-III to RUG-IV.
[20] That is, with the RUG-IV questionnaire, one can determine a patient's RUG-III code. However, with the RUG-III questionnaire, one cannot determine with certainty what a patient's RUG-IV classification would be.
[21] CMS' explanation for the downward rate adjustment appears in MedPAC's 2015 Report to the Congress on Medicare Payment Policy: http://www.medpac.gov/docs/default-source/reports/mar2015_entirereport_revised.pdf

2.2 SNF-hospital integration

Over time, the structure of the SNF industry has fluctuated in response to Medicare's policy changes. Vertically-integrated SNFs, i.e. SNFs owned by hospitals, were essentially nonexistent in the 1970s and early 1980s, when Medicare reimbursed hospitals on a cost-plus basis. When Medicare implemented the hospital prospective payment system in 1983, hospitals faced an incentive to discharge patients more quickly. At the same time, Medicare continued to reimburse SNFs on a cost-plus basis. Thus, many hospitals established or purchased SNFs as a discharge destination and revenue source. Vertically-integrated SNFs had higher costs than freestanding SNFs, and therefore higher reimbursement rates. The number of vertically-integrated SNFs peaked in 1998, at 2,173 facilities nationwide or 13.8 percent of all SNFs (Rahman et al., 2016). When Medicare adopted the SNF prospective payment system in 1998, it imposed a site-neutral payment system on both hospital-based and freestanding SNFs that did not recognize cost differences across the two settings other than those related to case-mix and geography.[22] By 2014, the number of SNFs owned by a hospital had fallen to about 800 or 5 percent of all SNFs (Rahman et al., 2016).

2.3 Self-referrals

A small body of research confirms the popular wisdom that providers are more likely to refer patients to co-owned providers. As noted above, Baker et al. (2016) find this is true for physicians employed in hospital-owned practices. Nakamura et al. (2007) show that "feeder" or community hospitals acquired by large tertiary care hospitals increase privately-insured referrals and decrease Medicaid referrals to their new tertiary owner, suggesting that newly acquired hospitals steer more profitable patients toward (and less profitable patients away from) their new hospital partner.

CMS attempts to protect patients from potential harm due to physician self-interest through regulations known as "Stark laws." The Stark laws generally prohibit "a physician from making referrals for certain healthcare services payable by Medicare if the physician (or an

[22] Medicare's rates for hospital based SNFs were roughly twice as high as the rates for other SNFs (Schieber et al., 1986). As a result, the decrease in Medicare rates for hospital-owned SNFs would have substantially affected profits even though Medicare is not the predominant payer of SNF care.

immediate family member) has a financial relationship with the entity performing the service."[23] Other provisions in Social Security law restrict hospitals from making referral decisions for explicit financial gain and enshrine Medicare patients' right to choose their providers.[24] Finally, anti-kickback regulations make it illegal to pay or receive "anything of value to induce or reward referrals or generate Federal health care program business."[25] Some hospitals report not sharing detailed data on SNF options with patients for fear of unduly influencing patients and running afoul of these regulations (Tyler et al., 2017). The Affordable Care Act prohibited physician self-referrals to newly formed physician-owned hospitals and restricted the expansion of such hospitals, in response to concerns about self-referrals and cherry-picking (Plummer and Wempe 2016). However, organizational self-referrals are typically not subject to the Stark laws because physicians are often not equity owners in practices owned by these organizations. Furthermore, self-referrals do not violate Stark laws, the anti-kickback statute, or antitrust laws under certain conditions such as common ownership and a sufficient degree of clinical integration among the various components of the organization.[26]

Self-referrals are also important in the context of payment models that incentivize hospitals to constrain patients' post-discharge spending. The Affordable Care Act encourages providers to form Accountable Care Organizations (ACO) to coordinate patient care and collectively share responsibility for patient outcomes; there have now been several "generations" of ACO models and in 2020, nearly 11 million Medicare enrollees received care from an ACO.[27] Medicare has also tested episode-based payment models for targeted conditions such as hip and knee replacements, holding hospitals financially accountable for the entire episode of care, not just the inpatient stay. Finally, Medicare discourages readmissions for specific conditions by linking hospital payments with readmission rates under the Hospital Readmission Reduction Program. These payment reforms incentivize hospitals to exert influence over patient care outside of their facilities. Insofar as self-referrals can improve coordination of care or reduce financial risk, payment reforms may also encourage referrals to internal or affiliated providers.

[23] https://www.cms.gov/newsroom/fact-sheets/modernizing-and-clarifying-physician-self-referral-regulations-proposed-rule
[24] 42 U.S.C. § 1320a-7b; 42 U.S.C. § 1395a
[25] https://oig.hhs.gov/compliance/provider-compliance-training/files/StarkandAKSChartHandout508.pdf
[26] https://news.bloomberglaw.com/health-law-and-business/kickback-referral-rules-coming-and-doctors-seek-clarity
https://www.cms.gov/newsroom/fact-sheets/modernizing-and-clarifying-physician-self-referral-regulations-proposed-rule
[27] https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/sharedsavingsprogram/about

Indeed, CMS has recently announced proposals to relax the Stark laws for providers in "value-based arrangements."[28]

3. Data

3.1 Medicare Data

Our main source of data is the 100 percent Medicare claims files from September 2007 to December 2012. We subdivide the data into hospital discharges, SNF discharges, and all other claims. Our primary focus is on hospital discharges (and the destinations of patients discharged), as we are interested in how patient profitability impacts the propensity for hospitals to self-refer patients to an integrated SNF. However, we also examine the effect of integration on patient outcomes, and in constructing those outcomes we make use of all claims within 90 days of a hospital discharge.

3.1.1. Inpatient Discharge Data

We match the Medicare hospital discharge claims to hospital-year data from the Medicare Cost Reports. We set aside the inpatient data from last quarter of 2007 and the first quarter of 2008 to calculate several "initial state" variables used in the analyses; we refer to this data as the "training sample."[29] We limit the sample during the study period (2008Q2 to 2012Q4) to discharges from hospitals with inpatient claims in each year from 2008 to 2012, inclusive.

We divide the 58 million discharges during this period into groups based on the discharging hospital's history of SNF ownership.[30] We define three groups of hospitals: (a) the treatment group, consisting of general acute care hospitals ("GACs") that own at least one SNF subprovider in all years from 2008 through 2012; (b) control group 1, consisting of critical access hospitals ("CAHs") that own a swing-bed SNF and never own a non-swing-bed SNF in all years from 2008 and 2012; and (c) control group 2, consisting of GACs that never own a SNF

[28] ibid

[29] Quarters correspond to quarters in a calendar year, e.g. quarter 1 corresponds to January through March.

[30] We define a SNF as owned by a hospital in a given year if the SNF is designated as a subprovider in the hospital's Medicare Cost Report. We also obtain hospital size, hospital ownership type, margin, and occupancy from the Medicare Cost Reports.

subprovider between 2008 and 2012.[31] Swing-bed SNFs are located within a hospital, and are comprised of beds that can be used either for inpatient or for SNF care. Crucially, Medicare reimburses for swing-bed SNFs within CAHs on a cost-plus basis, and therefore these SNFs were not subject to the price shock. We omit admissions to hospitals falling outside these three groups (about 16 percent of the total) from our analyses. We refer to the resulting sample of 47 million inpatient discharges as the "estimation sample." Tables A1 and A2 summarize the effect of each sample restriction on the number of claims and hospitals.

Each control group serves a different purpose. Control group 1 consists of CAHs that own a SNF, and thus can self-refer patients; they are particularly useful as a comparand for the impact of the price shock on the propensity to self-refer. However, control group 1 is not an appropriate comparand for studying the effect of self-referrals on outcomes. The price shock affects both self-referrals *and* SNF prices in the treatment group but does not affect SNF prices in control group 1. Control group 2 consists of GACs that do not own a SNF, and thus cannot self-refer patients; they are not useful as a comparand for the impact of the price shock on the propensity to self-refer. However, SNFs used by control group 2 patients were subject to the price shock. As a result, control group 2 hospitals allow us to control for the effect of the SNF prices on outcomes absent self-referrals.

3.1.2 SNF claims data

We use Medicare SNF claims data to link SNF stays to inpatient discharges. The SNF claims data include the dates of admission and discharge from the SNF, the patient's RUG code, and the amount that the SNF was reimbursed for the care (inclusive of Medicare's reimbursement, out-of-pocket payments, and any supplemental insurance payments).[32] We define "referrals" to SNFs as admissions commencing within 10 days of an inpatient hospital discharge.[33] In many analyses, we restrict the inpatient claims sample to the 9.3 million inpatient stays that are followed by a SNF referral.

[31] CMS designates certain rural hospitals as CAHs, which provides them benefits (e.g., cost-based reimbursement for Medicare services) as compared to GACs. Hospitals must meet requirements regarding size, distance to another hospital, and services provided in order to receive this designation.
[32] While patients are assigned to only one RUG code on any given day, this code may change at predetermined intervals. The SNF claims data includes all dates and corresponding RUG codes for each patient.
[33] Although Medicare reimburses SNF visits occurring within 30 days of a qualifying inpatient stay, we limit to SNF visits occurring within 10 days of a qualifying inpatient stay because our focus is steering by hospitals.

The SNF claims data does not contain the patient assessment data needed to assign patients to RUG codes. That data is present in a separate Medicare file called the SNF Minimum Data Set (MDS). As previously noted, the patient assessment used to construct RUG-III codes is not forward compatible with the patient assessment used to construct RUG-IV codes, meaning it is not possible to assign patients treated under the RUG-III system to a RUG-IV code. However, the patient assessments are backwards compatible, i.e., given the information on a patient's assessment under the RUG-IV system, it is possible to construct the patient's RUG-III code.

To create an estimate for how the RUG update mechanically altered reimbursements, we accessed the MDS data for the three quarters following the RUG update (excluding the first quarter under the RUG-IV system, i.e. we used data from the first three quarters of calendar year 2011.[34] During that time, reimbursement was based on each patient's RUG-IV code, but patients were also assigned to a RUG-III code in the MDS. The difference between the RUG-III and RUG-IV code assignments for this fixed sample of patients occurs solely because of changes in CMS's algorithm for assigning patients to RUGs; both the RUG-III and RUG-IV assignments are based on the same patient assessment data.

To isolate the component of a patient's post-update price change that is solely "mechanical" (i.e., untainted by potential changes in SNF behavior or patient composition), we use the sample of MDS data to construct the distribution of RUG-IV codes associated with each RUG-III code. When combined with data on RUG-III and RUG-IV prices, this allows us to construct an expected price change arising from the RUG update for each RUG-III code (for further detail, see the Data Appendix). We use this data as an input in constructing our price instrument, described in greater detail in Section 3.2 below.

Finally, we use SNF claims data to calculate the daily reimbursement paid for each SNF visit, which we refer to as $price$.

3.1.3 Other data

We also calculate total patient spending in the 90 days following discharge. Spending is the sum of "allowed amounts," which includes Medicare reimbursements, non-Medicare payer

[34] This data is discussed further in Data Appendix A. We omit data from the first quarter of the 2011 fiscal year in our estimation in order to account for any noise generated by SNF adoption of the new patient assessment system that supported the transition from RUG-III to RUG-IV.

reimbursements, and patient cost-sharing. We construct this measure by aggregating data from seven separate Medicare claims files: inpatient, SNF, carrier, durable medical equipment ("DME"), home health agency, hospice, and outpatient.[35] We use the Medicare Master Beneficiary Summary File to obtain patient demographic information, including age, race, sex, and date of death, where applicable. Finally, for our analysis of SNF acquisitions, divestitures, and entry, we obtain additional SNF-year data from the Brown University School of Public Health's Shaping Long-Term Care in America Project (LTCfocus.org), including total number of beds, for-profit status, and multi-facility chain status, over the period 2007-2017.[36]

3.2 Measuring patient profitability

We are interested in how relative differences in SNF patients' profitability affect self-referrals and patient outcomes. The most naïve measure of patient profitability would be the realized price for a patient. Such a measure is problematic for two reasons. First, patients assigned to different RUG codes differ in underlying health and healthcare needs, which may affect appropriate treatments and costs, and therefore profits. Second, even panel variation in price for a given RUG code is not generally exogenous to changes in costs because Medicare's annual updates to RUG reimbursement rates are intended to track changes in costs. However, the 2010 RUG update creates plausibly exogenous variation in patient-level reimbursements and—assuming providers did not change their costs dollar-for-dollar in response—profits.[37] In this section, we explain how we construct a patient-level measure of the change in reimbursement, which we call $pred\Delta price$.

As previously described, the RUG-III to RUG-IV reform changed the mapping of patient characteristics into RUG codes, the number of codes, and the prices associated with each code. Ideally, we would observe exogenous patient characteristics that could be used to assign each patient to a RUG-III code and a RUG-IV code. The difference between the patient's Medicare

[35] With two exceptions, we have access to the 100 percent sample of Medicare claims for each of these files. For the carrier and DME files, which primarily include claims from physicians, ambulatory surgery centers, and durable medical equipment providers, we only have access to a 20 percent sample. Thus, full patient spending data are only available for this subset of patients. In Table A8, we show that results are not substantially different for this subset and the 100 percent sample with carrier and DME costs excluded.

[36] Shaping Long Term Care in America Project at Brown University funded in part by the National Institute on Aging (1P01AG027296).

[37] Given Medicare is the payer for roughly 11 percent of SNF patient-days, it seems plausible that SNFs may not adjust their cost structure in a way that fully offsets these profit shocks.

reimbursement rate ("price") under these two systems could then serve as an instrument for the change in patient reimbursements after RUG-IV's adoption. However, SNF providers have incentives to distort patient characteristics reported on the RUG assessments (under either iteration) to maximize reimbursements, and therefore patients with similar characteristics (as recorded on a SNF claim) may have different true health states before and after the RUG update.

As a result, we do not rely on characteristics reported on SNF assessments or claims to determine the magnitude of the price shock on patients or to track similar patients over time. Instead, we leverage the fact that effectively all SNF stays follow an inpatient stay and inpatient claims contain detailed patient demographics and diagnoses that are unrelated to SNF reimbursements. Hospitals do not have any incentive to distort the patient characteristics reported on an inpatient claim in response to the reform.

As discussed above, we isolate the "mechanical" component of the RUG update (i.e., untainted by potential changes in SNF behavior) using data from the SNF MDS. We merge that data with inpatient claims data from October 2007 to March 2008, covering the two quarters *prior* to the start of our analysis sample, i.e. the "training sample" described earlier.

We regress the mechanical change in SNF reimbursement rates from the RUG update (calculated from the MDS) on a set of patient diagnostic and demographic information (from the inpatient data). We then use the estimated parameters to predict the price change for *all* patients in the broader estimation sample (i.e., all inpatient stays between 2008Q2 to 2012Q4). We call this variable $pred\Delta price$; further details on its construction are presented in Data Appendix A.

To understand our methodology, consider a concrete example. The RUG reform mechanically affected patient reimbursements based on a few dimensions of patient need, including the extent to which the patient required rehabilitation or compensatory nursing services. The RUG assessments elicit this information through questions about a patient's capacity to conduct various activities, such as tie shoes, self-feed, shower, or perform various levels of exercise or movement. To address the fact that SNFs might alter their responses to these questions because of a reimbursement rate change, we implicitly use the fact that the responses to these questions will be correlated with the information on the patient's inpatient admission, such as the patient's demographics, DRG code, and comorbidities.

For example, we expect the types of SNF services needed by a 70-year-old receiving a hip replacement to differ from the types of SNF services needed by an 80-year-old recovering from a major stroke. Indeed, the most common RUG-III code for the hip replacement patient is “RUL”, while the most common code for the stroke patient is “RUB.” Patients in both codes have roughly similar needs but with one crucial difference: patients with the “RUL” code need additional “extensive services,” such as IV medication or ventilator use. Thus, as expected, the “RUL” code carries with it a 12.5 percent higher reimbursement. The definition of “extensive services” changed in the RUG update, causing many patients who would have been coded as “RUL” under RUG-III to be coded as “RUB” patients under RUG-IV.[38] These patients became relatively less profitable to treat due to the RUG update. Our instrument is constructed solely from these mechanical variations in reimbursement induced by the RUG transition.

3.3 Patient Outcomes and Controls

We construct indicators for whether the patient is referred to a SNF within 10 days of discharge, and if so, whether that SNF is a subprovider of a hospital (i.e., self-referred). We also calculate 90-day total patient spending incurred after the inpatient discharge. We then take the natural logarithm and winsorize at the 1st and 99th percentiles for the relevant quarter. We also construct two separate clinical outcome measures, again at the patient-level: one for mortality and another for readmission, both within 90 days of the inpatient discharge.[39]

Finally, we develop three patient-level control variables to include in our regression models. The first, ln $(predicted\ spending)$, is constructed using the estimated parameters from a regression of logged post-discharge spending on a rich set of patient characteristics, diagnoses, and interactions of these terms, estimated on the “training sample” described earlier. The second two controls, $mortality\ risk$ and $readmission\ risk,$ are constructed analogously, using indicator variables for death or readmission within 90 days of hospital discharge, respectively. Each patient-level control is included in the model that uses the corresponding outcome as the dependent variable.[40] Further details are in Data Appendix B.

[38] This change is confirmed using the claims data. In 2011, the first full calendar year under the RUG-IV system, 70-year-old hip replacement patients are most commonly assigned the “RUA” and “RUB” codes (49 percent of patient days) and very few patients are assigned the “RUL” code. However, for 80-year-old stroke patients, the “RUB” continues to be one of the most common codes assigned, with 16 percent of such patients receiving the code for SNF care. Therefore, comparing the relative profitability of treating either group of patients, 70-year-old hip replacement patients became relatively less profitable to treat compared to 80-year-old stroke patients.

[39] Patient mortality is determined using the date of death reported in the Medicare Master Beneficiary Summary File. Patient readmission is determined using inpatient claims data.

[40] We include these composite measures in lieu of the individual regressors for computational ease.

3.4 Summary Statistics

Table 1 contains summary statistics in two panels: Panel A for all inpatient discharges in the estimation sample, and Panel B for inpatient discharges preceding a SNF stay.[41] Statistics are displayed separately for the treatment group (discharges from hospitals always owning a SNF), control group 1 (discharges from CAH hospitals with swing-bed SNFs), and control group 2 (discharges from hospitals never owning a SNF). Panel A shows that patients in control group 1 are likeliest to be referred to a SNF, with 28 percent of patients referred versus 21 percent for the treatment group and 18 percent for control group 2.[42] Panel B shows that conditional on subsequently entering a SNF, patients admitted to hospitals in control group 1 have fewer comorbidities and are less likely to be Black than patients in the treatment group. Patients in control group 2 are similar to those in the treatment group.

Table A3 presents hospital-level descriptive statistics for the treatment and control groups.[43] Treatment group hospitals tend to be larger than hospitals in control group 1, but smaller than hospitals in control group 2. They are more likely to be for-profit than hospitals in control group 1 (18.3 versus 6.2 percent), but less likely to be for-profit than hospitals in control group 2 (18.3 versus 27.1 percent). Treatment group hospitals are more likely to be located in the South than hospitals in either control group.[44] Treatment group hospitals have higher profit margins than hospitals in control group 1, but lower margins than hospitals in control group 2.[45] Similarly, treatment group hospitals have higher occupancy than hospitals in control group 1, but lower occupancy than hospitals in control group 2. The median household income within a hospital's zipcode is lower in treatment group hospitals than control group 1 hospitals ($45,333 vs. $52,711), but higher compared to hospitals in control group 2 ($45,333 vs. $41,389). Given these differences across patients and hospitals in each group, our models incorporate a rich set of patient characteristics, as well as hospital fixed effects.

Figure 1 displays the distribution of $pred\Delta price$ for our estimation sample. All patients had a positive $pred\Delta price$, with a range of 9.5 percent to 20 percent and an average of 14.7

[41] In the interest of space, panel A includes only the subset of measures most relevant for the entire sample of discharges. Admissions occurring during the transition to RUG IV (2010Q2) are excluded from the regression models and therefore also excluded from Table 1.
[42] Figure A1 shows there is substantial heterogeneity in self-referral rates among treatment group hospitals.
[43] Figure A2 illustrates heterogeneity in select characteristics across the treatment and control groups.
[44] Hospital regions are defined using U.S. Census designated regions (https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf).
[45] Profit margins are calculated as an average of margins from 2005-2007.

percent.[46] To better understand the correlates of $pred\Delta price$, Table A4 presents summary statistics separately for patients with above and below-median values of $pred\Delta price$. Patients with $pred\Delta price$ above the median are three times as likely to be dually-eligible for Medicaid, more than twice as likely to be Black, and have a 36 percent lower Charlson comorbidity index (i.e. *fewer* comorbidities) than patients below the median. These statistics suggest the RUG update could be used to study the impact of reimbursement changes on racial and socioeconomic disparities in health care, an avenue that is outside the scope of our paper but is an important area for future research.

In addition, patients with high $pred\Delta price$ are more likely to be referred to a SNF, but less likely to be self-referred. Thus, variation in $pred\Delta price$ is not captured by a unidimensional measure of patient health such as mortality risk. Table A5 shows how $pred\Delta price$ varies across the 15 most common inpatient diagnoses for SNF-referred patients in the estimation sample. The vast majority of patients with diagnoses such as major hip and knee joint replacement or chronic obstructive pulmonary disease typically have below median $pred\Delta price$, while the opposite is true for patients with kidney and urinary tract infections or nutritional disorders. Even diagnoses that are categorically similar have different $pred\Delta price$ variation. For example, patients with hip procedures excluding major hip replacement are very likely to have high $pred\Delta price$. Similarly, pneumonia patients can expect below median $pred\Delta price$ while those with other respiratory infections typically have above median $pred\Delta price$.

These statistics motivate our inclusion of hospital-specific interactions with $pred\Delta price$. These interactions eliminate potential sources of bias arising from differences across hospitals in patient composition and outcomes.

4. Estimation

4.1. First stage analysis

We begin by exploring the validity of our instrument for SNF price. We estimate the following equation:

[46] Recall that Medicare subsequently reduced all SNF reimbursement rates in the year following the RUG update. Our analysis relies on cross-patient variation in the shock, rather than on the level.

$$(1) \qquad ln\ (price_{it}) = \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \sum_{q \in [-9,9]} \beta^2_q \cdot \mathbb{1}_{h,t=q+\tau} \cdot pred\Delta price_i + \varepsilon_{it}.$$

where i indexes individuals, t indexes the quarter in which an individual was discharged from the hospital, $h(i)$ denotes the discharging hospital, and $pred\Delta price$ is the predicted price shock for individual i. τ denotes the "transition quarter," the quarter prior to the RUG update. Patients discharged during the transition quarter may have had their SNF care partially reimbursed under the RUG-IV system, and are dropped from all regression analyses. $\mathbb{1}_{h,t=q+\tau}$ represents a set of indicator variables for the 9 quarters before and after the transition quarter. The coefficients of interest are represented by β^2_q, which capture the evolution of the impact of $pred\Delta price$ on actual price. To achieve identification, we restrict β^2_{-1}, the coefficient for the period prior to τ (April 2010 to June 2010), to 0.

Equation (1) also includes hospital-quarter fixed effects ($\beta^0_{h(i)t}$) and hospital-specific coefficients on $pred\Delta price$ ($\beta^1_{\mathrm{h(i)}}$). These terms are important controls for the second-stage regression, hence they are also included in the first stage. The hospital-quarter fixed effects control for unobservable, time-varying factors potentially correlated with outcomes, such as changes in hospital quality or general trends in discharge to post-acute care. The hospital-specific coefficient on $pred\Delta price$ controls for any time-invariant differences in outcome measures across hospitals that might also be correlated with the price shock. For example, the coefficients allow for the possibility that the link between patient mortality risk and unobserved hospital quality is correlated with the patient's price shock.

Figure 2 graphs the estimates of β^2_q from equation (1), depicting the relationship between $ln(price)$ and $pred\Delta price$ in each quarter relative to the period two quarters prior to the price shock. The coefficients are near zero before the price shock, increase to greater than one in the first quarter under the RUG update (further discussion of this magnitude is below), and then decrease to near one three quarters after the reform.[47] The decrease is the result of CMS's downward adjustment of overall SNF prices, described previously, but the association between actual and predicted price remains quite large.

In Table A6 and many analyses that follow, we report the coefficient estimates from a parsimonious version of equation (1):

[47] The estimates of β^2_1 and β^2_9 from equation (1) are statistically distinguishable at p<0.001.

$$(2) \qquad ln\,(price_{it}) = \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \beta^2 \cdot Quarter_t \cdot pred\Delta price_i + \beta^3 \cdot Post_t \cdot pred\Delta price_i + \beta^4 \cdot Post_t \cdot Quarter_t \cdot pred\Delta price_i + \varepsilon_{it},$$

$Quarter$ is a continuous variable that allows for a linear time trend. $Post$ is an indicator that is equal to 1 in all quarters after the transition quarter. The coefficients of interest are β^3 and β^4, which capture post-shock changes in outcome levels and trends for patients with differing values of $pred\Delta price$.

Barring a shock-induced change in SNF referral patterns or measurement error, β^3 should be close to 1. Column (1) of Table A6 shows that our estimate is 1.24 and is statistically significantly greater than 1. The coefficient of interest falls below 1 upon the addition of SNF-quarter fixed effects (see column (2) of Table A6 and Figure A3. Thus, changes in SNFs to which patients are referred magnifies the effect of the reimbursement shock on total spending ("price" of a SNF visit). Note our preferred specifications exclude SNF-quarter fixed effects as changes in SNF referral patterns are the effect of interest.

4.2. The Impact of Price on Self-Referral

We assess how changes in patient profitability impact the propensity of vertically integrated hospitals to self-refer patients. We estimate a version of equation (1) with the binary outcome variable $self\text{-}referral$, which takes on a value of 1 if a patient is self-referred. We conduct this analysis on two separate samples, the treatment group and control group 1, the sample of CAHs with swing-bed SNFs which are exempt from the RUG payment system and therefore did not experience the same changes in SNF reimbursement levels. Figure 3 depicts the time-varying relationship between $self\text{-}referral$ and $pred\Delta price$ separately for the treatment group and control group 1. There is no apparent pre-period trend for either group, i.e. there is no indication that patients with higher values of $pred\Delta price$ experience significant changes over time in the rate at which they are self-referred among either set of discharging hospitals in the 2 years leading up to the price shock. However, during the post-reform period, the propensity for self-referral increases for the treatment group and decreases for the control group.

A change in self-referral rates could be due to an increase in the rate of any referral to a SNF, an increase in the rate of self-referral conditional on any referral, or some combination of the two. To disentangle the potential sources of the observed increase in self-referral correlated with $pred\Delta price$, we estimate equation (1) expanding the sample to include all inpatient discharges and using the binary outcome variable $SNF\ referral$, which takes on a value of 1 if a patient is referred to any SNF. Figure 4 depicts the time-varying relationship between $SNF\ referral$ and $pred\Delta price$ separately for the treatment group and control group 1. There are no changes in this relationship timed with the reform; the increase in self-referral appears entirely due to the reallocation of relatively more profitable SNF patients to owned facilities, rather than to a change in the likelihood such patients are referred for SNF care.[48]

To determine whether the differences in self-referral patterns between the treatment and control groups are statistically distinguishable, we pool the treatment group and control group 1 and estimate a variant of equation (2), which includes additional interactions for patients in the treatment group:

$$
\begin{aligned}
(3) \qquad self\text{-}referral_{it} = {} & \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i \\
& + (\beta^2 \cdot \text{Quarter}_t + \beta^3 \cdot Post_t + \beta^4 \cdot Post_t \cdot \text{Quarter}_t) \cdot pred\Delta price_i \\
& + (\beta^5 \cdot \text{Quarter}_t + \beta^6 \cdot Post_t + \beta^7 \cdot Post_t \cdot \text{Quarter}_t) \cdot pred\Delta price_i \cdot GAC_{h(i)} \\
& + \varepsilon_{it}
\end{aligned}
$$

where $GAC_{h(i)}$ takes on a value of 1 if the patient is discharged from a hospital in the treatment group (i.e., general acute care hospitals) and 0 if the patient is discharged from a hospital in control group 1 (i.e., CAHs). The coefficients of interest are β^6 and β^7, which reflect the extent to which patients with higher values of $pred\Delta price$ are likelier to be referred to a SNF owned by their discharging hospital following the price shock in the treatment group as compared to the control group. The estimates, reported in column (1) of Table 2 (see shaded rows), show a statistically significant break from trend in the treatment group as compared to the control group. To ease interpretation, Table 2 includes an estimate for the combined effect of the treatment in the final quarter of our analysis (i.e., the fourth quarter of 2012).[49] Column (2) of Table 2 shows that this increase in self-referrals is not driven by increases in overall SNF referrals.[50]

The magnitude of this effect is large: a one percentage point change in predicted price increases a hospital's propensity to self-refer a patient by 0.8 percentage points. Given the

[48] Pooled regression results (displayed in Table 2) confirm no post-period differences in self-referrals between treatment and control groups.

[49] The effect of the treatment in the final quarter of our analysis is calculated by adding the coefficient on $Post \cdot pred\Delta price \cdot GAC$ and 8 multiplied by the coefficient on $Post \cdot Quarter \cdot pred\Delta price \cdot GAC$.

[50] The specification using *SNF referral* as the dependent variable includes a patient-level risk-adjustment factor, denoted *SNF referral risk*. Results are not sensitive to its inclusion. Additional details are in Data Appendix B.

probability of self-referral in the treatment group is 32.6 percentage points during the pre-period, this response corresponds to a self-referral elasticity of 2.5.[51]

4.3. The Impact of Self-Referral on Outcomes

Next, we examine whether self-referral affects 90-day post-discharge mortality, the likelihood of readmission, and overall spending, using the price shock as an instrument for self-referral. An instrument is appropriate given the possibility that self-referral depends on unobserved characteristics that may also be correlated with outcomes; indeed, Appendix Table A7 demonstrates that self-referred patients are different along observable dimensions (e.g., they are more likely to be black, Medicaid-eligible and female.) Recall that the RUG update affected both prices as well as the odds of self-referral; both could independently affect outcomes. To separate these two channels, we contrast the effects of $pred\Delta price$ on patients in the treatment group with the effects on patients in control group 2, who were admitted to SNFs following stays in general acute care hospitals that do not own a SNF. These patients by definition cannot experience any change in self-referral rates, but the receiving SNFs in both groups are exposed to the price shocks.

We augment our specifications by including a patient-level risk-adjustment factor, denoted X_i, for the relevant outcome (see Data Appendix B for additional details).[52] We again begin with a specification that allows for quarterly interactions with $pred\Delta price$:

$$Y_{it} = \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \sum_{q\in[-9,9]} \beta^2_q \cdot \mathbb{1}_{h,t=q+\tau} \cdot pred\Delta price_i + \alpha \cdot X_i + \varepsilon_{it}, \tag{4}$$

where Y represents $mortality$, $readmission$, and $ln\ (spending)$, as previously defined. For models using $ln\ (spending)$ as the dependent variable, we weight each observation by $predicted\ ln\ (spending)$, which is estimated based on patient and hospital data from the patient's inpatient stay.[53]

[51] We find that a percentage point change in price (.01 units of $pred\Delta price$) leads to an increase of 0.81 percentage points in $selfref$. Given the average self-referral rate of .326, this is an increase of 2.49 percent. Thus. the self-referral elasticity ($(\%\Delta selfref)/(\%\Delta price)$) is 2.49/1 = 2.49.
[52] Results with and without these patient-level risk-adjustment factors are similar across all patient outcome specifications.
[53] The weighting is to better reflect what happens to total spending. Results from unweighted specifications are similar.

Figure 5 depicts the estimated coefficients on the quarterly interaction terms, separately for the treatment group and control group 2. While visual inspection suggests similar trends between the two groups for all three outcome measures, regression results obtained from pooling the treatment and control groups and testing the differences in levels and trends between the two (presented in Table A9) reveal slight differences in pre-trends for one of the outcome measures, $readmission$.[54] Given this violation in the parallel trends assumption, we proceed with analyzing only $mortality$ and $ln\ (spending)$. We find no statistically significant differential effects of $pred\Delta price$ on the treatment group relative to the control group for either of these outcomes.

In Table 3 we estimate the effect of self-referral on mortality and spending using two-stage least squares instrumental variable regressions. Formally, we estimate the following first-stage model,

$$
\begin{aligned}
self\text{-}referral_{it} = {} & \gamma^0_{h(i)t} + \gamma^1_{h(i)} \cdot pred\Delta price_i \\
& + (\gamma^2 \cdot \text{Quarter}_t + \gamma^3 \cdot Post_t + \gamma^4 \cdot Post_t \cdot \text{Quarter}_t) \cdot pred\Delta price_i \\
& + (\gamma^5 \cdot \text{Quarter}_t + \gamma^6 \cdot Post_t + \gamma^7 \cdot Post_t \cdot \text{Quarter}_t) \cdot pred\Delta price_i \\
& \cdot OwnSNF_{h(i)} + \alpha \cdot X_i + \varepsilon_{it},
\end{aligned} \tag{5}
$$

and second-stage model,

$$
\begin{aligned}
Y_{it} = {} & \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i \\
& + (\beta^2 \cdot Quarter_t + \ \beta^3 Post_t + \beta^4 \cdot Post_t \cdot Quarter_t) \cdot pred\Delta price_i \\
& + \beta^5 \cdot Quarter_t \cdot pred\Delta price_i \cdot OwnSNF_{h(i)} + \beta^6 \cdot \widehat{self\text{-}referral_{it}} + \alpha \cdot X_i \\
& + \eta_{it}.
\end{aligned} \tag{6}
$$

The variables capturing the differential impact of the predicted price change in the post period for hospitals that own SNFs (i.e., $Post \cdot pred\Delta price \cdot OwnSNF$ and $Post \cdot Quarter \cdot pred\Delta price \cdot OwnSNF$) relative to hospitals that do not serve as instruments for $self\text{-}referral$ the identifying assumption being that these measures affect outcomes only through their impact on the probability of self-referral.[55] Table 3 presents the IV estimates of the effect of self-referral on $mortality$ and $ln(spending)$. Neither estimate is statistically distinguishable from zero, and

[54] The regression specifications are analogous to equation (3), but $GAC_{h(i)}$ is replaced with $OwnSNF_{h(i)}$, an indicator for patients admitted to hospitals in the treatment group versus control group 2.

[55] We perform weak identification tests by calculating Kleibergen-Paap rkWald F statistics of 10.690 and 9.239 for the $mortality$ and $ln(spending)$ models respectively. Using standard Stock-Yogo weak identification test critical values for 2 instrumental variables and 1 endogenous regressor, given a nominal test size of 5%, the cutoff for 10% maximal IV size is 11.59 and the cutoff for 15% maximal IV size is 8.75.

the confidence intervals are wide. We are unable to rule out economically meaningful increases or decreases in these outcomes.[56,57]

5. Heterogeneity and Robustness

5.1. Heterogeneity by Hospital Characteristics

We explore whether hospitals with different characteristics vary in the extent to which they increase self-referrals in response to the price shock. To do so, we re-estimate the self-referral model (equation (2)) with additional terms that allow the effect of $pred\Delta price$ in the pre- and post-period to vary by a set of hospital characteristics, generally measured as of 2007. These characteristics include region, ownership type, size, profit margin, and occupancy rate.[58,59] For each characteristic, we report the combined effect of the treatment in the final quarter in Appendix Table A10. We find that no characteristic is significantly associated with a heterogenous response at the 5-percent level.[60] However, there is some evidence ($p<0.10$) that hospitals with higher occupancy rates have a more muted response to the reimbursement shock. A one-standard-deviation increase in occupancy rate (i.e., 0.17) reduces the coefficient on $pred\Delta price$ in Q42012 by more than 40 percent.

5.2 Potential Hospital Behavioral Responses

In conducting our main analyses, we calculate $pred\Delta price$ by relying only on diagnoses and demographics from an individual's inpatient stay. This approach removes any behavioral responses of the receiving SNF to the price shock, which, if correlated with self-referring

[56] Estimating an OLS version of equation (6) for $mortality$ and $ln(spending)$, we find that $selfref$ is negatively associated with both outcomes. For $mortality$, the coefficient (standard error) on $selfref$ is -0.06 (0.0008) and, for $ln(spending)$, the coefficient (standard error) on $selfref$ is -0.35 (0.002).
[57] For readmission, we find that the coefficient on $Quarter \cdot pred\Delta price \cdot OwnSNF$ is -0.01, statistically significant at the 10 percent level, indicating differences in trends in the pre-period.
[58] We classify each hospital based on data from the earliest year it appears in our Cost Reports data, which is typically 2007. Ownership type is not-for profit, for-profit, or government-owned. Size is small (<100 beds), medium (100-199 beds), or large (>200 beds).
[59] Because data on profit margins is noisy, we use the 3-year average over 2005-2007.A small number of hospitals report negative revenues (due to large adjustments) or profit margins greater than 1. We remove such hospitals from the analysis and winsorize profit margins within each year at the 1st and 99th percentiles before computing the 3-year average.
[60] Using an alternative estimation method where each characteristic is considered in a separate regression, we similarly find no statistically significant (at the 5-percent level) heterogeneous response across categories.

behavior, could yield biased estimates of the impact of self-referral on outcomes. Our estimation strategy thus relies on the assumption that hospitals lack an incentive to manipulate *inpatient* diagnoses based on the SNF reimbursement rate. To confirm that hospitals did not respond to the price shock by systematically changing DRG coding behavior to assign more patients to DRGs that tend to yield higher (or lower) SNF reimbursement rates, we examine whether inpatient diagnoses responded to the SNF price shock. We first construct a measure of $sim\Delta price$ at the DRG-level ($pred\Delta price'$); details are in Data Appendix A. Next, we create counts for the number of patients corresponding to each hospital-DRG-quarter triad ($PatientPop$).[61] Finally, we estimate the association between quarterly values of $PatientPop$ and $pred\Delta price'$.[62] We find no systematic change in this effect around the time of the RUG update (Figure A4).

5.3. Robustness to the Hospital Readmissions Reduction Program

In 2010, the Affordable Care Act established the Hospital Readmissions Reduction Program ("HRRP") to incentivize hospitals to reduce readmissions for Medicare patients. Beginning in October 2012, hospitals faced penalties for high risk-adjusted thirty-day readmission rates among patients admitted to targeted DRGs. The introduction of the HRRP could bias our estimates if targeted DRGs have systematically higher or lower values of $pred\Delta price$ or self-referrals, as in that case, the estimated effects could reflect a response to HRRP. To examine this possibility, we excluded patients admitted to HRRP-targeted DRGs from the estimation sample and re-estimated our principal model. We find the estimated relationship between $pred\Delta price$ and self-referrals is relatively unchanged.[63]

5.4. Robustness to Changes in Patient Composition

Although we control for a host of patient characteristics via individual patient risk adjusters, it remains possible that changes in the composition of the inpatient population

[61] In order to account for hospital-DRG pairs that have no patients in certain quarters, we construct a balanced dataset across time for each hospital-DRG pair. That is, if a given hospital has a patient in a given DRG in any quarter, we construct an observation for all quarters.
[62] The specification also contains hospital-quarter fixed effects and hospital-DRG fixed effects.
[63] The key result showing an increase in the post-shock relationship between $pred\Delta price$ and self-referral rates is graphed in Figure A5. Using equation (2) with $selfref$ as the dependent variable, the effect of the price shock in the final quarter of our analysis is 0.63 with a standard error of 0.14. Re-estimating this specification excluding HRRP-targeted DRGs, the effect of the price shock in the final quarter is 0.52 with a standard error of 0.16. The differences in these estimates is not statistically significant.

correlated with both $pred\Delta price$ and the propensity for self-referral are creating a spurious result. To examine this hypothesis, we calculate a risk-adjustment score for self-referral, $selfrefrisk$, and estimate the time-varying impact of $pred\Delta price$ on $selfrefrisk$.[64] We find no changes in this relationship concurrent with the price shock.[65]

6. Discussion and Conclusions

6.1 Assessing the Economic Magnitude of the Estimated Increase in Self-Referral

Having found that vertically integrated hospitals responded to Medicare's price changes by cherry-picking patients, steering those who became more (less) profitable post-shock toward their own (other) SNFs, we now consider the magnitude of this response.

As previously noted, our estimated coefficients and average pre-shock self-referral rate imply the elasticity of self-referral with respect to price is 2.5. This is a rather large effect, considering the numerous other factors that affect referral decisions. By comparison, prior research implies the elasticity of self-referral with respect to a patient's distance to an integrated SNF (relative to an unintegrated SNF) is much lower—approximately 0.5.[66]

Second, we compare the price increase captured by vertically integrated hospitals through changes in self-referral behavior to the theoretical maximum price increase they could have captured had they admitted those patients with the highest ranking values of $pred\Delta price$ to their own SNFs during the post-shock period, holding their total SNF admissions constant.[67,68] We

bed in Data Appendix B.
[65] These results appear in Figure A6.
[66] We estimate this elasticity using figures presented in Rahman et al. (2016). While the authors do not directly estimate the effect of distance on SNF choice, they present estimates of the impact of differential distance to a vertically integrated hospital (vs. an unintegrated hospital) on the likelihood of admission to an integrated SNF (relative to admission to an unintegrated SNF). They find the average self-referral rate is 0.12, and the effect of a one percent increase in the distance to a VI hospital on visiting a VI SNF is -0.0579.
[67] We calculate the price increase captured by each hospital-quarter in four steps. First, we use specification (2) with $self\text{-}referral$ as the outcome to predict actual patient-level self-referral. Second, to predict counterfactual patient-level self-referral in the absence of a response to the policy, we set $Post = 0$ for all observations. Third, for each patient, we subtract the predicted counterfactual self-referral from the predicted actual self-referral and multiply by $pred\Delta price$. Finally, we average the value from step three across patients within each hospital-quarter.
[68] We calculate the maximal price increase a hospital could capture in three steps. First, for each quarter, we compute the average self-referral rate for all vertically integrated hospitals. Then, we construct two scenarios, one where patients with the lowest $pred\Delta price$ are self-referred and another where for patients with the highest $pred\Delta price$ are self-referred. Finally, we compute the average $pred\Delta price$ for each of these groups and take the difference.

estimate vertically integrated hospitals realized 48 percent of this theoretical maximum.[69] This estimate suggests a sizeable cherry-picking response.

Third, we find that the total increase in payments captured by vertically integrated hospital-SNF entities as a result of their change in self-referral patterns was financially meaningful. On average, we estimate that these entities earned an additional $175 (in 2012 dollars) per SNF-referred patient, solely as a result of post-shock changes in self-referral behavior.[70] Given average SNF revenues of around $16,000 per patient in 2012, the change in self-referral patterns yielded an estimated increase in profit margins of 1 percent, a significant boost considering the all-payer average profit margin was below 2 percent in 2012 (and has declined since, per MedPAC estimates in 2014 and 2019).

6.2 Does Integration Impact Viability of Independent SNFs?

Our analyses reveal that integrated hospitals successfully reallocate downstream SNF referrals, boosting their own margins at the expense of their rivals. Given this finding, we now consider whether hospital-SNF integration threatens the viability of independent rivals. We are unable to exploit the RUG update to study whether changes in cherry picking incentives induced the exit or contraction of independent facilities because we lack sufficient information about these incentives prior to the update.[71] Thus, we pursue a different empirical strategy: we examine the impact of hospitals' acquisitions and divestitures of SNFs (i.e., their integration and dis-integration decisions) on exit decisions of independent SNFs.

For this analysis, we study exit decisions by independent SNFs that admitted Medicare patients in both 2008 and 2009. For each independent SNF, we calculate a measure of its

[69] Estimations are based on 2012Q4.

[70] We define patient-level "base" SNF spending as predicted SNF spending computed solely using patient demographics in the training sample (see detailed methodology in Data Appendix B). We do not use actual SNF spending due to endogenous responses to the price shock.

[71] The RUG update shifted relative prices, but without information on absolute patient profitability, we are unable to ascertain whether the relative price changes attenuated or exacerbated cross-patient differences in profitability. Consider a simplified world with two patients. Patient A is reimbursed $105 per day and patient B is reimbursed $100 per day in the pre-period, but patient B sees a 5% shock to prices in the post-period. If we assume that treatment costs equal reimbursements in the pre-period, then there are no gains from cherry-picking between patient A and B in the pre-period, while those gains materialize in the post-period due to the shock. However, if we assume that costs are equal across patients in the pre-period, then there are gains from cherry-picking in the pre-period but no such gains in the post-period. Thus, while the RUG update allows us to study steering due to *relative* changes in profitability, it cannot tell us whether the absolute gains to cherry picking were higher in the pre-period or the post-period

"exposure" to vertically integrated (VI) SNFs as of 2009, denoted $initial\ VI\ exposure_s$. This measure, constructed using zipcode-level market shares and volumes in 2008-9 among all zipcodes from which s admitted patients, is defined as the number of patients that would divert to s from integrated SNFs if integrated SNFs were removed from patients' choice sets, divided by the total number of s' patients. It captures the competitive significance of integrated competition for every SNF s at the start of the study period. To measure the impact of changes in exposure due to divestitures (or acquisitions) of integrated rivals, we construct $\Delta VI\ exposure_{s\tau}$ by predicting the share of s' patients that would divert to (or from) independent SNF s in year τ.[72,73,74] We calculate $\Delta VI\ exposure$ for each independent SNF in the sample in each year between 2008 and 2017. Additional details on the construction of $\Delta VI\ exposure_{s\tau}$, and a table of summary statistics for this exit analysis, are included in Data Appendix C.

We estimate linear probability models for the decision of an independent SNF to exit in any given year as a function of $\Delta VI\ exposure_{s\tau}$, controlling for $initial\ VI\ exposure_s$.[75] To ensure a clean "pre-treatment" period, we exclude SNFs that are exposed to acquisition/divestiture of VI SNFs during the first two years of the study period (2008-9).[76] We begin by estimating a model that includes three leads and lags of $\Delta VI\ exposure_{s\tau}$, and controls for $initial\ VI\ exposure_s$. Our estimating equation takes the following form:

[72] $\Delta VI\ exposure_{s\tau}$ takes on positive values for acquisitions and negative values for divestitures, and its observed range is -1.37 to 1.09. During our study period, most transactions are divestitures so $\Delta VI\ exposure_{s\tau}$ is typically negative.

[73] The date of such VI transactions are defined as the first year in which a new VI status is recorded in the Cost Reports.

[74] VI transactions are restricted to: (a) acquisitions of already existing SNFs, or (b) divestitures of SNFs that continue operations for at least one year. Said differently, we do not consider new SNFs created by hospitals as acquisitions, nor do we consider SNFs completely closed by hospitals as divestitures. These restrictions are necessary to show that our estimated effect on independent SNF exit is a result of changes in VI status to nearby SNFs and not a result of changes in local SNF capacity (due to entry and exit of rivals). We consider the effects of net entry/exit through the measure described below, $\Delta competitor$.

[75] Estimating a Cox hazard model with SNF exit as the outcome yields very similar results.

[76] Thus, we exclude SNFs with non-zero values of $\Delta VIexposure_{s\tau}$ in 2008 or 2009. This restriction excludes 5,036 of 13,858 independent SNFs operating in both 2008 and 2009. The estimation sample reflects the annual exit decisions of the remaining 5,823 SNFs. 5 of these SNFs are acquired by hospitals by 2017; we exclude these SNFs from the estimation sample beginning in the year of acquisition, leading to 21 dropped observations.

$$exit_{st} = \beta^0 + \beta_t^1 + \beta_{r(s)}^2 + \sum_{y \in [-3+,3+]} \beta_y^3 \cdot \mathbb{1}_{s,\mathrm{t=y+\tau}} \cdot \Delta VI\ exposure_{s\tau} + \beta^4 \cdot initial\ VI\ exposure_s$$
$$+ \left[\sum_{y \in [-3+,3+]} \beta_y^5 \cdot \mathbb{1}_{s,\mathrm{t=y+\tau}} \cdot \Delta competitor_{s\tau} + \beta_s^6 \cdot X_s \right] + \varepsilon_{st} \tag{7}$$

where s indexes independent SNFs, t indexes years, and $r(s)$ indexes a SNF's Census Region. The leads of $\Delta VI\ exposure_{st}$ test the parallel trends assumption – i.e., that exit probabilities do not change in anticipation of changes in VI exposure; the lags show the magnitude and timing of potential responses to these changes.[77] We also present results obtained when adding the bracketed term, which includes a vector of SNF characteristics measured as of 2008 (denoted X_s), and leads and lags of $\Delta competitor_{s\tau}$, a capacity-based measure of the net entry/exit of rivals in SNF s's service area.[78] This measure controls for omitted, time-varying local factors that might impact the probability of exit and could potentially bias the coefficients of interest if also correlated with hospitals' integration decisions.

We graph the leads and lags of interactions with $\Delta VI\ exposure_{s\tau}$ from equation (7) in Figure 6.[79] The graph shows an elevated propensity for exit in the years following an increase in VI exposure; this increase is statistically significant (p<0.05) in the year the transaction is recorded as well as in year 1, after which exit patterns begin to return to pre-shock levels.

Table 4 displays the coefficient estimates from both the parsimonious and expanded specifications. The coefficients of interest are minimally affected by inclusion of additional controls.[80]

The point estimates imply the average value of $\Delta VI\ exposure$ has a small impact on the probability of exit in the year of, and in the year following, the transaction.[81] However, SNFs

[77] The leads/lags for three or more years before/after a transaction are pooled together.
[78] The SNF characteristics are for-profit status, chain membership, number of beds, and number of beds squared. Additional details on the construction of $\Delta competitor$ is presented in Data Appendix C.
[79] Figure 6 presents coefficient estimates from specification 7 without the bracketed term. Table 4 shows these coefficients are very similar across specifications.
[80] Ceteris paribus, for-profit SNFs and smaller SNFs are likelier to exit. SNFs are less likely to exit 2 or more years prior to the entry of a rival; this pattern is suggestive of common positive demand shocks reducing the odds of exit and encouraging net entry.
[81] The average absolute value of $\Delta VI\ exposure$ is .01, conditional on it being non-zero. If negative, as is typically the case in the data, an exposure of this magnitude is predicted to reduce the cumulative probability of exit in the year of a divestiture and year 1 by around 0.063 percentage points, or 4.3 percent of the average probability of exit over two years. Using a Cox hazard model produces similar estimates for the impact of $\Delta VI\ exposure$ on exits. A $\Delta VI\ exposure$ value of -.01 reduces the exit hazard by 3.7 percent in the year of a divestiture and by 4.3 percent in the following year.

with relatively large absolute values of $\Delta VI\ exposure$ experience significant changes in their probability of exit. For example, the 588 SNFs with transactions falling in the bottom 5 percent tail of $\Delta VI\ exposure$, i.e. independent SNFs heavily exposed to divestitures of integrated SNFs, experience a decrease in their probability of exit of 0.2 percentage points in the year of and following the transaction. This decrease is about 17 percent of the sample probability of exit during any consecutive two years.[82]

This analysis suggests that vertical integration of hospital-SNFs reduces the viability of independent SNFs. Although these results do not speak directly to the impact of new integration (or dis-integration) on quality or costs, the earlier analyses find no evidence of such benefits for the marginal patient redirected to an integrated SNF.

6.3 Conclusions

Overall, our analyses paint a discouraging picture of the effects of vertical integration of hospitals and SNFs. In the wake of a 2010 reform inducing price shocks that varied at the individual level, we find that vertically integrated hospitals steered patients who became relatively more profitable toward their own SNFs, disadvantaging independent SNFs. In a separate analysis, we find that independent SNFs are less likely to exit when integrated hospitals in their market area divest a SNF (and it remains open). Last, we find no evidence that self-referral improves patient outcomes or reduces Medicare spending. Together, these facts raise concerns that vertical integration in healthcare could harm consumers by enabling integrating organizations to foreclose upstream inputs to rivals and increasing rivals' likelihood of exit. Such concerns could presumably form a basis for antitrust challenges of vertical consolidation in healthcare markets, and fuel engagement by other stakeholders who may be in a position to scrutinize, deter, or reshape vertical arrangements and transactions.

[82] The average probability of exit within two consecutive years (.015) is used as the sample probability of exit.

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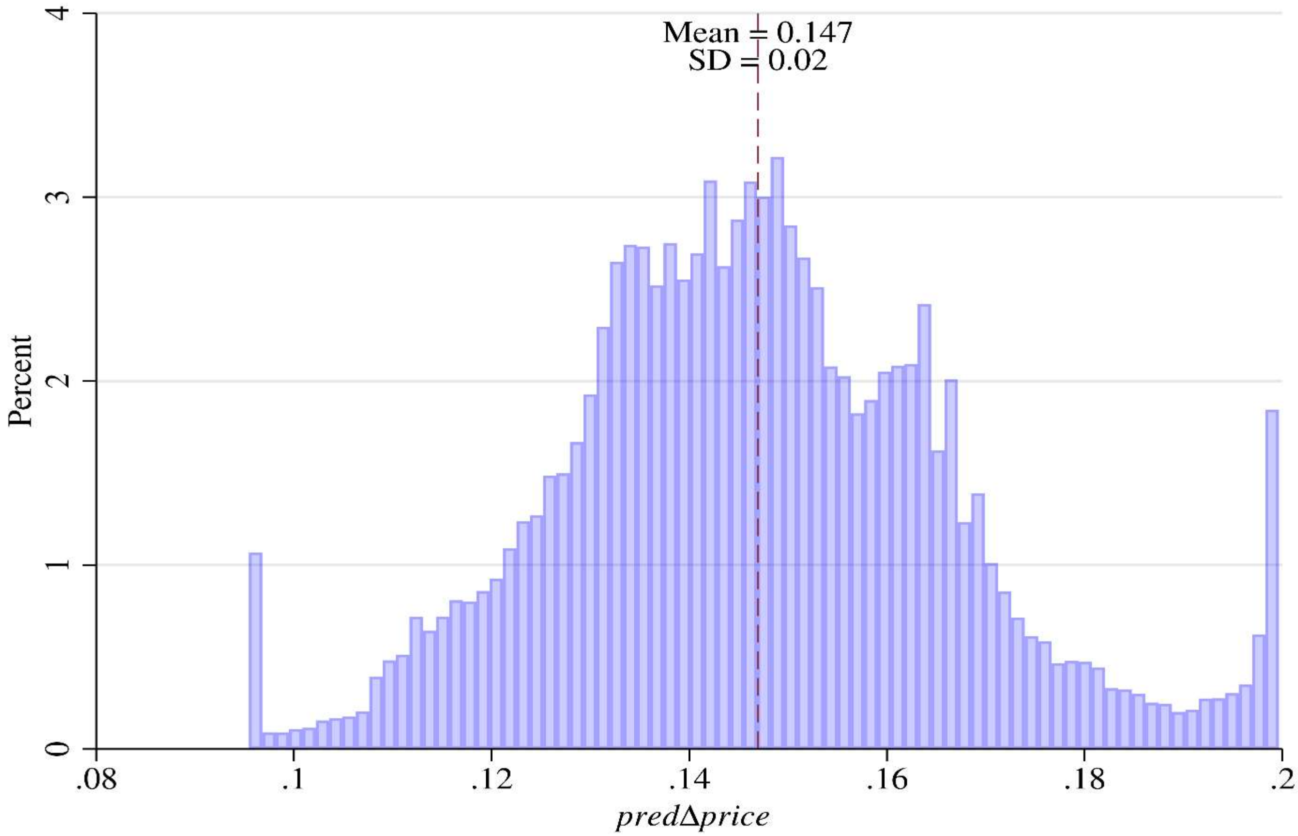
Table 1: Patient characteristics by sample group

Panel A: All inpatient stays	(1) Treatment group: GACs with owned SNFs	(2) Control group 1: CAHs with owned SNF swing-beds	(3) Control group 2: GACs without owned SNFs	Difference (1)-(2)	Difference (1)-(3)
Referral to any SNF	0.212	0.283	0.184	-0.071***	0.028***
	[0.409]	[0.451]	[0.388]		
Hospital stay >=3 days	0.711	0.654	0.703	0.056***	0.008***
	[0.453]	[0.476]	[0.457]		
N	10,294,981	1,274,338	33,824,275		
Panel B: Stays resulting in referral to a SNF				(1)-(2)	(1)-(3)
Price	420.490	-	464.280	-	-43.791***
	[120.140]	[-]	[114.626]		
Demographics					
Age	79.337	81.270	-	-1.933***	-
	[10.897]	[10.343]	[-]		
Female	0.641	0.646	0.635	-0.005***	0.005***
	[0.480]	[0.478]	[0.481]		
Black	0.102	0.039	0.109	0.063***	-0.008***
	[0.302]	[0.193]	[0.312]		
Dual-eligibility	0.360	0.366	0.323	-0.005***	0.037***
	[0.480]	[0.482]	[0.468]		
Charlson comorbidity index	1.330	1.203	1.325	0.127***	0.005***
	[1.512]	[1.388]	[1.528]		
N	2,130,853	360,852	6,078,266		

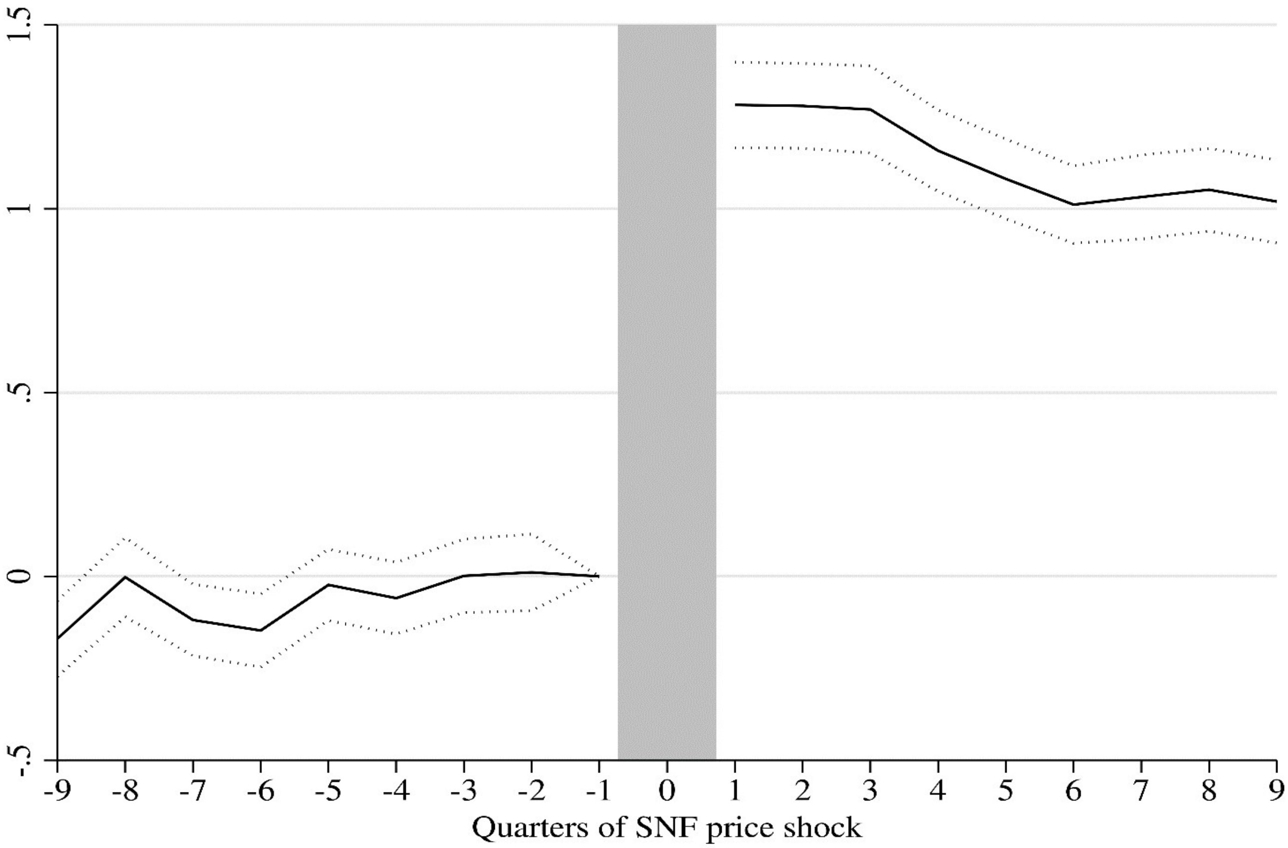
Notes: Table reports sample means for each variable. Standard deviations appear in brackets immediately beneath. Differences in means across samples are presented in the last two columns. Stars denote the result of a two-sample t-test for difference in means: * p<0.10, ** p<0.05, *** p<.01. The unit of observation is an inpatient Medicare discharge from hospitals within each sample group. Observation are restricted to only those that report all relevant variables. Further, patients with admissions occurring during the transition to RUG IV (2010Q2), which are excluded from the regression models, are omitted. Price is the average daily reimbursement for the SNF stay. Price is not observed for patients in control group 1, as swing-bed SNFs owned by critical access hospitals are not subject to Medicare's SNF prospective payment system and thus have no daily reimbursement rate for patients.

Figure 1: Distribution of pred∆price



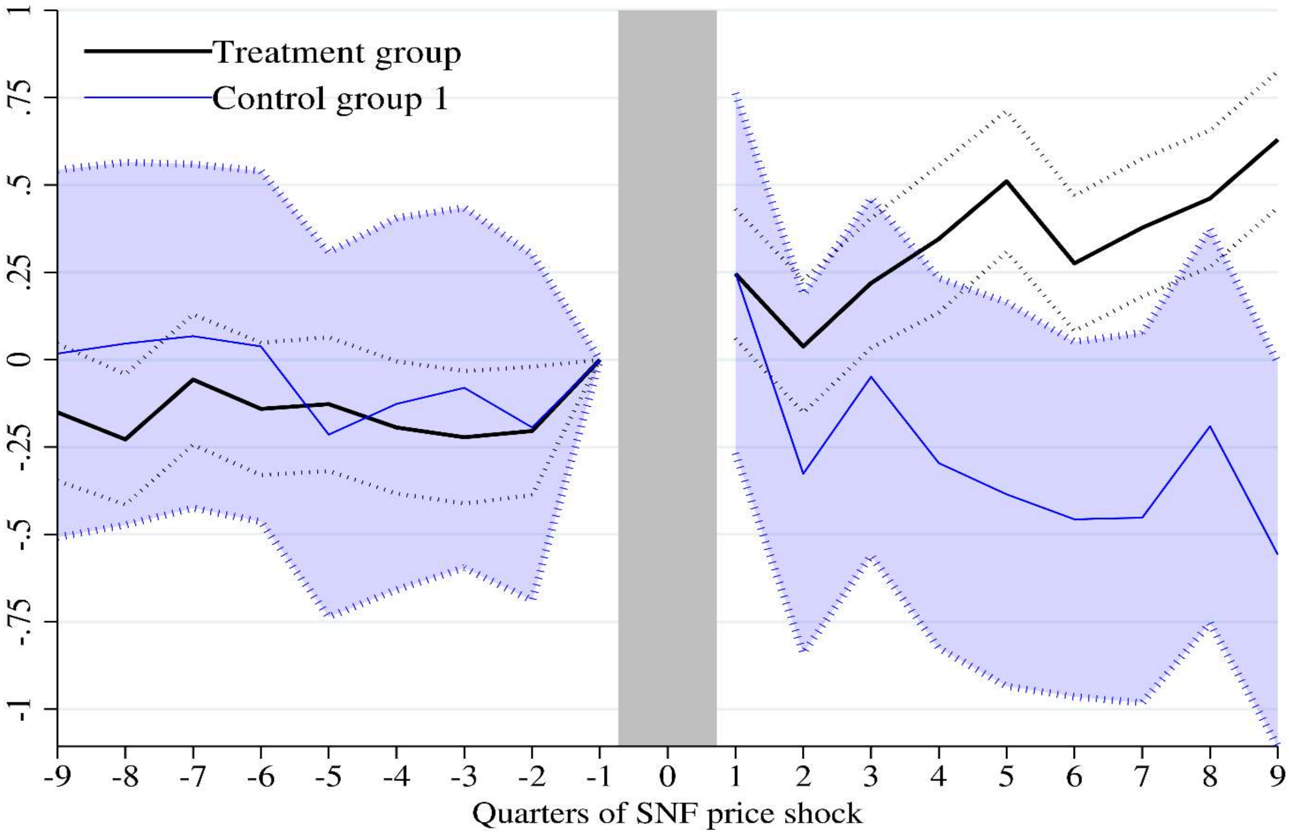
Notes: Figure reflects the distribution of *pred∆price* among patients in the estimation sample. The unit of observation is an inpatient Medicare discharge. Values of *pred∆price* are winsorized at the 1st and 99th percentiles.

Figure 2: Relationship between *pred∆price* and *ln(price)*



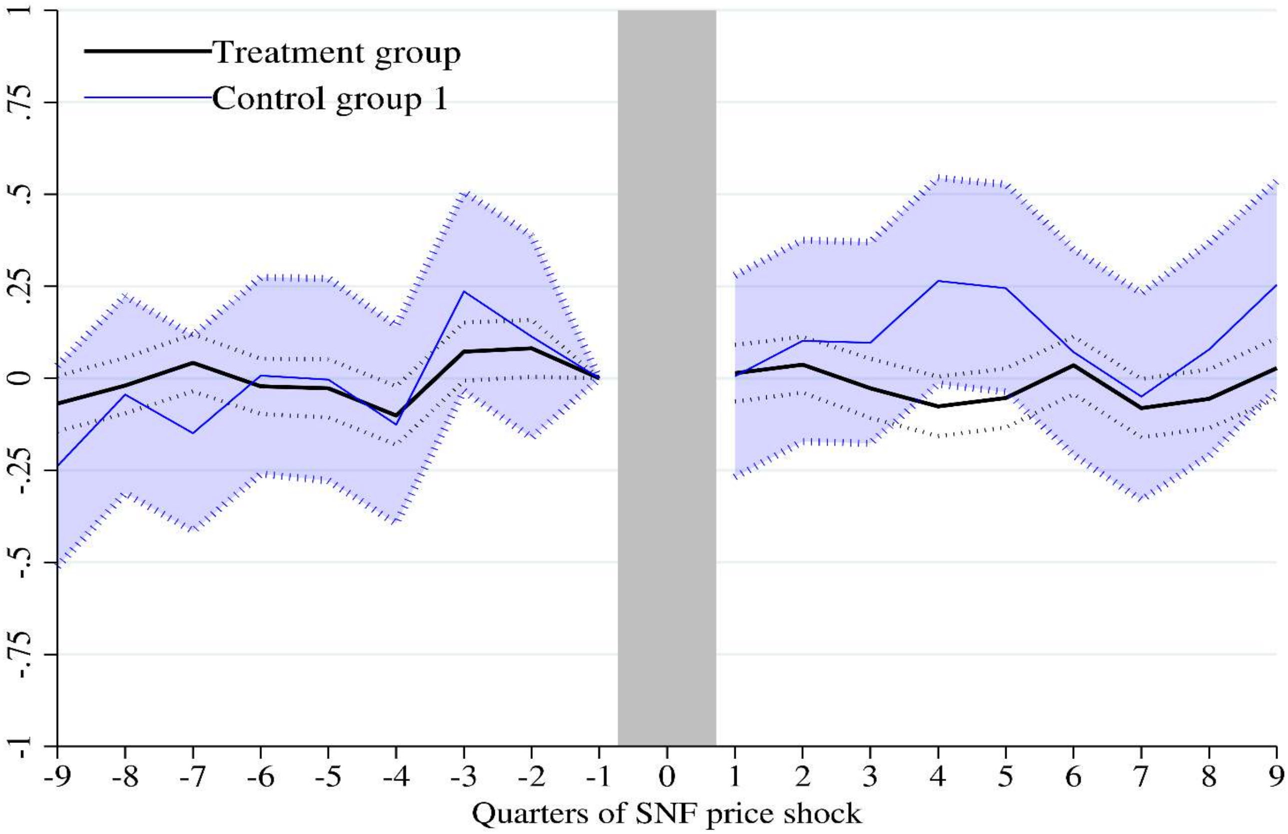
Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price,* obtained from estimating equation (1) in the text. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price* . The unit of observation is an inpatient Medicare discharge. The sample includes only discharges from treatment group hospitals to SNFs. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price* ; and (2) hospital-quarter fixed effects.

Figure 3: Effect of *pred∆price* on self-referral



Notes: Each solid line plots the coefficient estimates on the lags and leads of *pred∆price,* obtained from estimating equation (3) in the text. The dependent variable is an indicator variable for admission to a SNF owned by the discharging hospital. The dotted lines and the light blue shaded area represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price* . The unit of observation is an inpatient Medicare discharge. The sample includes only discharges from hospitals in the treatment group and control group 1 referred to SNFs. Each model includes: (1) interactions between hospital-specific indicator variables and pred∆price; and (2) hospital-quarter fixed effects.

Figure 4: Effect of *pred∆price* on SNF referral



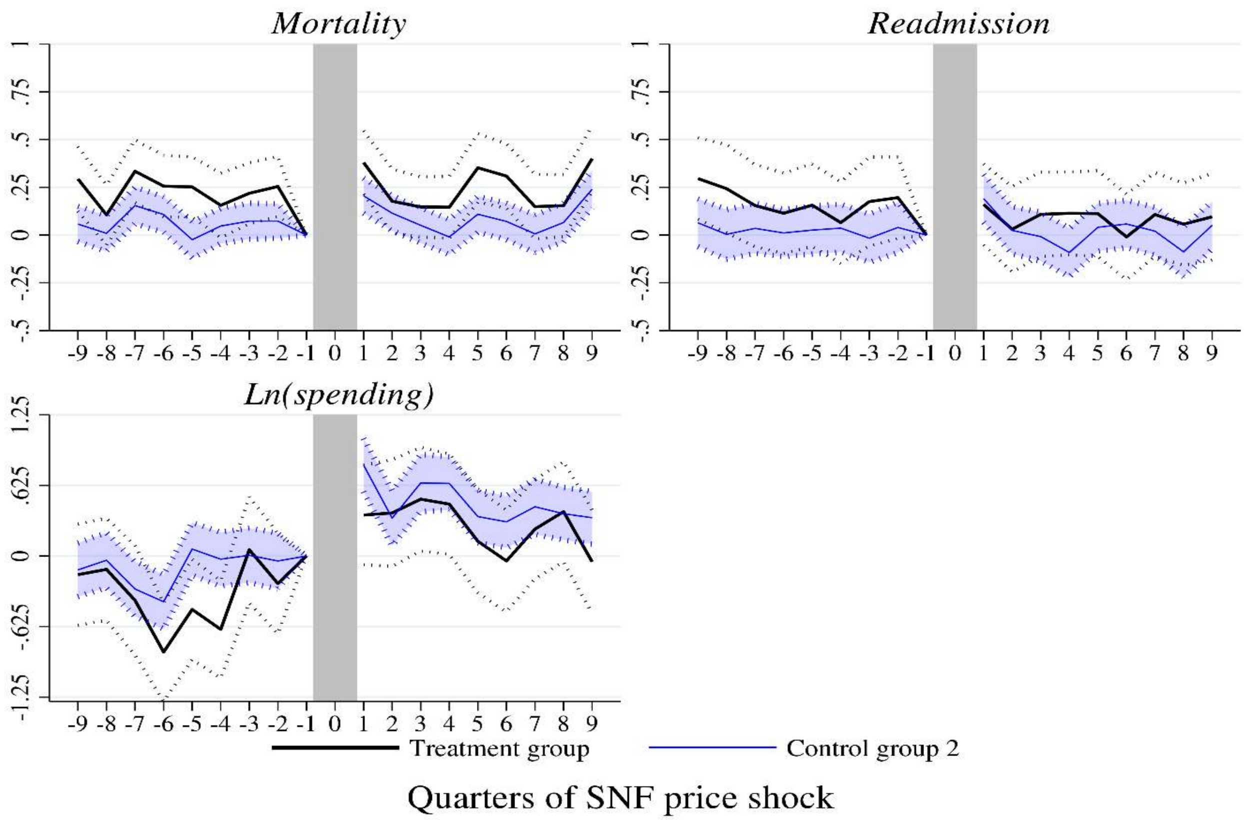
Notes: Each solid line plots the coefficient estimates on the lags and leads of *pred∆price,* obtained from an equation analogous to equation (3) in the text but substituting an indicator for any SNF referral as the dependent variable. The dotted lines and the light blue shaded area represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price* . The unit of observation is an inpatient Medicare discharge. The sample includes discharges from hospitals in the treatment group or control group 1. Each model includes: (1) interactions between hospital-specific indicator variables and *pred∆price* ; (2) hospital-quarter fixed effects; and (3) *SNF-referral risk* , a patient-level prediction for *SNF-referral* .

Table 2: Effect of *pred∆price* on referrals

	(1) Self-referral	(2) SNF referral
Post · pred∆price · GAC	0.101	0.043
	[0.195]	[0.107]
Post · Quarter · pred∆price · GAC	0.089	0.014
	[0.037]**	[0.019]
Quarter · pred∆price · GAC	0.027	-0.026
	[0.025]	[0.013]*
Post · pred∆price	0.156	-0.099
	[0.185]	[0.105]
Post · Quarter · pred∆price	-0.042	-0.027
	[0.036]	[0.018]
Quarter · pred∆price	-0.022	0.035
	[0.024]	[0.013]***
SNF referral risk		1.040
		[0.002]***
Combined effect of price shock for GAC in 2012Q4	0.811	0.154
	[0.387]**	[0.198]
Dependent variable mean	0.339	0.220
Observations	2,547,401	11,552,525

Notes: * p<0.10, ** p<0.05, *** p<.01. The unit of observation is an inpatient Medicare discharge. Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are reported in brackets. The combined effect gives the impact of the price shock on the outcome for GACs relative to CAHs in 2012Q4. The sample of hospitals include general acute care (GAC) hospitals that own a SNF from 2008 to 2012 and critical access hospitals (CAH) that only own swing-bed SNFs from 2008 to 2012. In column (1), the patient sample is restricted to inpatient discharges referred to SNFs. In column (2), the patient sample includes all patients. Further, patients missing *SNF referral risk* are dropped from column (2).

Figure 5: Effect of pred∆price on patient outcomes



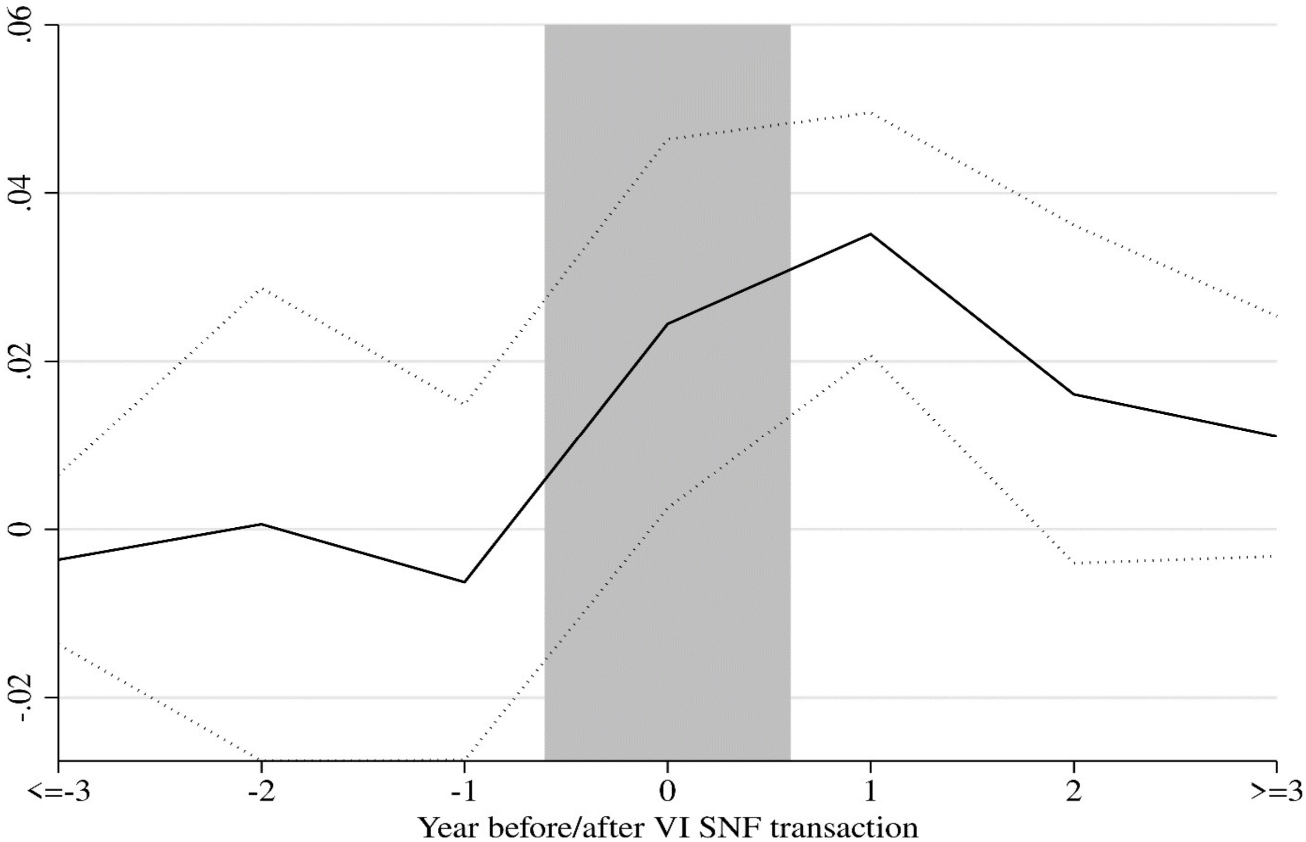
Notes: Each solid line within a panel plots the coefficient estimates on the lags and leads of *pred∆price* from equation (4) in the text, using different outcomes within 90-days of discharge as the dependent variable. The dotted lines and the light blue shaded area represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The unit of observation is an inpatient Medicare discharge. The sample includes only discharges from hospitals in the treatment group and control group 2 referred to SNFs. Each model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; (2) hospital-quarter fixed effects; and (3) a patient-level prediction for the outcome.

Table 3: Effect of self-referral on 90-day health outcomes

	Mortality			*Ln(spending)*		
	(1)	(2)	(3)	(4)	(5)	(6)
	First-stage (Outcome: Self-referral)	Reduced form	IV	First-stage (Outcome: Self-referral)	Reduced form	IV
Self-referral			0.295			0.301
			[0.213]			[0.564]
Post · predΔprice · OwnSNF	0.270	0.061		0.258	0.099	
	[0.070]***	[0.073]		[0.073]***	[0.178]	
Post · Quarter · predΔprice · OwnSNF	0.046	0.017		0.042	0.008	
	[0.013]***	[0.013]		[0.013]***	[0.031]	
Quarter · predΔprice · OwnSNF	0.004	-0.013	-0.014	0.005	-0.014	-0.015
	[0.009]	[0.009]	[0.010]	[0.009]	[0.022]	[0.025]
Post · predΔprice	-0.004	0.068	0.064	-0.000	0.571	0.577
	[0.001]***	[0.035]*	[0.034]*	[0.000]*	[0.083]***	[0.080]***
Post · Quarter · predΔprice	-0.000	0.004	0.005	0.000	-0.069	-0.070
	[0.001]	[0.007]	[0.007]	[0.000]	[0.015]***	[0.014]***
Quarter · predΔprice	0.001	-0.005	-0.005	0.000	0.030	0.030
	[0.000]***	[0.004]	[0.004]	[0.000]***	[0.011]***	[0.011]***
Mortality risk	-0.063	0.900	0.918			
	[0.001]***	[0.003]***	[0.014]***			
Predicted ln(spending)				-0.006	0.835	0.837
				[0.002]***	[0.007]***	[0.007]***
Kleibergen-Paap rk Wald F Statistic	10.690			9.239		
Dependent variable mean	0.080	0.185	0.185	0.080	9.810	9.810
Observations	8,378,641	8,378,641	8,378,641	8,418,055	8,418,055	8,418,055

Notes: * p<0.10, ** p<0.05, *** p<.01. The unit of observation is an inpatient Medicare discharge. Observations in *ln(spending)* specifications are weighed by patient-level predicted spending (unlogged). Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred*Δ*price*; (2) and hospital-quarter fixed effects. Standard errors clustered by *pred*Δ*price* are in brackets. Columns (3) and (6) report IV regressions of the effect of self-referral on outcomes, with the predicted price shock for treatment group hospitals in the post-period—*Post · pred*Δ*price · OwnSNF* and *Post · Quarter · pred*Δ*price · OwnSNF*—serving as instruments for self-referral. The sample of hospitals include general acute care hospitals that own a SNF from 2008 to 2012 (indicated by *OwnSNF*) and general acute hospitals that never own a SNF from 2008 to 2012. Patients missing the relevant patient-level risk-adjustment factor are dropped.

Figure 6: Relationship between Δ*VI exposure* and exit by independent SNFs



Notes: The solid line plots the coefficient estimates on the lags and leads of Δ*VI exposure* , obtained from estimating equation (7) in the text. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered at the SNF level. The unit of observation is an independent SNF-year and the dependent variable is an indicator for exit. The sample of SNFs is restricted to independent SNFs operating in 2008-9 which were not exposed to changes in vertical integration during 2008-9. The specification also includes (1) *initial VI exposure,* the SNF's exposure to VI SNFs in 2008-2009; (2) year fixed effects; (3) and Census region fixed effects.

Table 4: Effect of Δ*VI exposure* on *exit*

	(1)	(2)	(3)
ΔVI exposure · (y = -3+)	-0.004	-0.004	-0.005
	[0.005]	[0.005]	[0.005]
ΔVI exposure · (y = -2)	0.001	-0.000	-0.000
	[0.014]	[0.014]	[0.014]
ΔVI exposure · (y = -1)	-0.006	-0.007	-0.005
	[0.011]	[0.011]	[0.011]
ΔVI exposure · (y = 0)	0.024	0.024	0.022
	[0.011]**	[0.011]**	[0.011]**
ΔVI exposure · (y = 1)	0.035	0.034	0.032
	[0.007]***	[0.007]***	[0.007]***
ΔVI exposure · (y = 2)	0.016	0.015	0.011
	[0.010]	[0.010]	[0.010]
ΔVI exposure · (y = 3+)	0.011	0.010	0.005
	[0.007]	[0.007]	[0.007]
Initial VI exposure	0.002	0.001	0.001
	[0.001]	[0.001]	[0.001]
For-profit		0.003	0.003
		[0.001]***	[0.001]***
Chain		-0.001	-0.001
		[0.001]	[0.001]
Beds		-0.000	-0.000
		[0.000]***	[0.000]***
Beds squared		0.000	0.000
		[0.000]**	[0.000]**
Δcompetitor · (y = -3+)			0.002
			[0.001]**
Δcompetitor · (y = -2)			0.005
			[0.001]***
Δcompetitor · (y = -1)			0.002
			[0.002]
Δcompetitor · (y = 0)			-0.008
			[0.006]
Δcompetitor · (y = 1)			0.003
			[0.002]
Δcompetitor · (y = 2)			0.007
			[0.004]*
Δcompetitor · (y = 3+)			0.006
			[0.002]***
Dependent variable mean	0.006	0.006	0.006
Observations	58,209	58,199	58,199

Notes: * p<0.10, ** p<0.05, *** p<.01. The unit of observation is a SNF-year. The sample includes independent SNFs in 2008-2009 that did not have any exposure to VI transactions in 2008 and 2009. Unreported controls include: (1) year fixed effects; and (2) Census region fixed effects. *y* indexes years before/after exposure year. *Initial VI exposure* and ΔVI exposure measures the magnitude of a SNF's exposure to VI SNFs in 2008-2009 and VI transactions, respectively. Δ*Competitor* measures the magnitude of a SNF's exposure to net exit/entry of rivals in the year of the exit/entry.