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Vertical Integration and Cream Skimming of Profitable Referrals: The Case of Hospital-Owned Skilled Nursing Facilities
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ABSTRACT

We examine whether vertical integration of hospitals and skilled nursing facilities (SNFs) could lessen competition by foreclosing rival SNFs' access to lucrative referrals. We find that it could: among integrated providers, a one percent increase in SNF reimbursement for a given patient discharged from the upstream hospital increases the self-referral rate to the hospital's downstream SNF(s) by 1.8 percent. We find no evidence of offsetting benefits for patients and payers: these increased self-referrals have an imprecisely estimated zero effect on patient outcomes and Medicare spending.

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There is sizeable empirical literature examining the effects of horizontal integration among direct competitors in healthcare settings, particularly hospitals. This literature finds that horizontal combinations typically lead to higher prices and spending for downstream patients and payers, without improvements in the quality of care.[1] For several decades, antitrust enforcers have challenged horizontal healthcare transactions using the principles outlined in the *Horizontal Merger Guidelines* issued jointly by the Federal Trade Commission (FTC) and the Antitrust Division of the Department of Justice (DOJ) in 2010, with a strong record of success particularly in the last 15 years.

There is a growing literature on vertical integration of providers at different stages of the value chain, particularly hospital-physician affiliations (e.g., Capps, Dranove, and Ody 2018; Neprash, Chernew, Hicks, Gibson, and McWilliams 2015; Baker, Bundorf, and Kessler 2014; Robinson and Miller 2014; McWilliams et al. 2018; Whaley, Zhao, and Richards 2021).[2] These studies find that hospital-physician affiliations also result in higher prices and spending, with no improvements in the quality of care. To date, however, neither federal enforcement agency has challenged a healthcare provider merger on vertical grounds, potentially emboldening industry participants who infer that vertical transactions are unlikely to receive much scrutiny.

In December 2023, the FTC and DOJ issued the *Merger Guidelines*, which deliberately omits "Horizontal" from the title and supplants the *Horizontal Merger Guidelines.* The new *Merger Guidelines* explicitly discusses the mechanisms through which vertical mergers may lessen competition. These include limiting access of rivals to intermediate or complementary products, services, or "routes to market," thereby weakening or foreclosing rivals in a "relevant market." Like the *Horizontal Merger Guidelines*, the new *Merger Guidelines* underscores that the Clayton Act proscribes acquisitions where "the effect of such acquisition may be substantially to lessen competition, or to tend to create a monopoly (15 U.S. Code § 18). The phrasing suggests post-merger consumer harm (e.g., increases in spending following hospital acquisition of an outpatient clinic or a skilled nursing facility) alone is unlikely to be viewed by

[1] For a comprehensive summary of the economic literature on consolidation in healthcare settings, see "Environmental Scan on Consolidation Trends and Impacts in Health Care Markets," *RAND* Research Report, September 2022.

[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.

the federal agencies as sufficient grounds for a merger challenge. After all, post-merger increases in prices and spending could arise for reasons apart from the lessening of competition proscribed by 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). Similarly, "mechanical" price changes may occur because of payer reimbursement schedules, which often have different prices for the same service delivered in different settings (Dranove and Ody 2019; Song, Wallace, and Neprash 2015). Due to the multiple possible explanations for price and spending increases, existing research on vertical combinations may not provide sufficient empirical evidence to bolster antitrust challenges of such vertical mergers.

We aim to fill this gap by examining one of the primary mechanisms for vertical integration to lessen competition, and therefore to form the basis for a challenge under the Clayton Act: foreclosure of inputs—in this case, patients —to a rival in a downstream market. We examine whether hospitals that own skilled nursing facilities (SNFs), which provide post-acute care to some patients following discharge, are likelier to self-refer more profitable patients. Such cream-skimming could undermine rival SNFs' incentive or ability to compete and could weaken them and result in their exit. We further examine whether any increase in self-referrals leads to changes in patient outcomes or total spending; if present, improvements in outcomes or reductions in total spending could partially or wholly offset any harm from a lessening of downstream competition. Antitrust enforcers consider these effects, known as "efficiencies," when deciding whether to challenge a transaction.

We focus specifically on patients enrolled in Medicare, the government-run health insurance program in the United States primarily serving individuals 65 or older and those with certain disabilities. Patients covered by Medicare are financially important to SNFs. Medicare enrollees account for a disproportionate share of SNF revenues and have historically been profitable to treat relative to the largest segment of SNF patients: enrollees in Medicaid, the U.S. public insurance program for low-income individuals. SNF care also plays a critical role in post-acute care for Medicare enrollees. Nearly 1 in 5 Medicare patients are discharged to a SNF following an inpatient stay, and SNF spending accounts for about half of Medicare's spending on post-acute care (MedPAC 2018; MedPAC 2019).

Using claims data for all "traditional" (fee-for-service) Medicare enrollees admitted to general acute-care hospitals (GACs) between 2008-2012, we explore whether vertically integrated hospital-SNFs altered self-referral patterns in response to a 2010 reimbursement reform that changed the relative profitability of patients. Because of the possibility of behavioral responses by SNFs to the new reimbursements, we isolate the plausibly exogenous component of the reimbursement change by calculating the change in predicted reimbursements for each patient based on characteristics of their *inpatient* admission, which precedes all SNF admissions reimbursed by Medicare. Consistent with our assumption, we find no evidence that vertically integrated hospitals altered inpatient characteristics, including admission diagnoses, in response to the SNF update.

We find that integrated hospitals increased the self-referral rate of patients that became relatively more profitable due to the shock, a result consistent with potential foreclosure of rival unintegrated SNFs. To assess whether a more arms-length vertical relationship yields similar patterns, we compared changes in referral rates to a hospital's most-preferred SNF for hospitals that are vertically integrated with their most-preferred SNF with changes in referral rates to a hospital's most-preferred SNF for a matched set of unintegrated hospitals. We find that only the integrated hospitals responded to the shock by referring patients who became relatively more profitable to their most-preferred SNF: looser vertical ties do not engender the same conduct as financial integration.

Our estimates imply the financial benefits to integrated hospital-SNF entities from steering more profitable patients to their own SNFs are substantial. We estimate SNFs earned an additional \$175 per self-referral induced by the 2010 reform, boosting profit margins on these referrals by 1 percentage point, a substantial increase relative to baseline, all-payer profit margins during this period of around 2 percent.

We then examine the impact of self-referral on patient spending and health outcomes using the reimbursement shock as an instrument for the likelihood of self-referral. SNF self-referrals may reduce patient spending if vertical integration allows for smoother patient transitions from the hospital to the nursing facility, leading to fewer care disruptions and adverse events which would contribute to additional spending. Self-referrals could also improve outcomes by easing the transfer of information between facilities when transitioning care. On the other hand, preferential referral to integrated SNFs could result in higher patient spending, as observed with hospital-physician affiliations. For example, integrated SNFs may not invest as heavily in quality of care as unintegrated SNFs because they are effectively guaranteed self-referrals from their integrated upstream hospital(s), and the reduction in care quality could raise total patient spending post-discharge and impact clinical outcomes. Alternatively, the easier transfer of patient information may enable integrated SNFs to more easily identify patients who can tolerate additional therapy services, which could also drive up spending and impact outcomes. Additionally, integrated SNFs may be less concerned with hospital readmission and transfers as this generates more revenue for the hospital-SNF system. Thus, the effects of an increase in self-referral on spending and patient outcomes are a priori ambiguous.

We find no evidence that self-referral induced by the 2010 reform improved clinical outcomes (specifically, 90-day mortality and readmission rates) or affected the total cost of care in the 90 days following discharge. However, the estimates are imprecise, and we are unable to rule out meaningful changes. Overall, these findings suggest vertical integration among acute and post-acute providers may lessen competition through cream-skimming of profitable referrals without offering offsetting benefits for patients and payers.

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, Capps, and Dranove (2007) and Barro, Huckman, and Kessler (2006). Nakamura, Capps, and Dranove (2007) find “feeder” or community hospitals acquired by large tertiary care hospitals increased referrals of patients with private insurance to their new tertiary owner but decreased referrals of patients with insurance through Medicaid, a public insurance program for low-income patients. Barro, Huckman, and Kessler (2006) 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 a vertical setting (i.e., between upstream providers of acute care and downstream providers of post-acute care) and occurs even for more subtle profit differentials (i.e., within a payer type).

Our work also complements prior studies on hospital-SNF referrals. Doyle, Graves, and Gruber (2017) find that patients treated at hospitals with higher proclivities to discharge to SNFs experience higher post-discharge spending and mortality.[3] Three studies find positive effects of

[3] Doyle, Graves, and Gruber (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.

self-referral on patient outcomes, reflected in reduced lengths of SNF stays (Rahman, Norton, and Grabowski 2016) and lower readmission rates (David, Rawley, and Polsky 2013; Konetzka, Stuart, and Werner 2018), but higher post-discharge spending (Konetzka, Stuart, and Werner 2018). Our study differs from these studies in that we isolate the impact of receiving treatment via self-referral to a vertically integrated SNF; that is, the empirical strategy eliminates potential treatment effects associated with differences among hospitals that elect to become vertically integrated.

Last, the findings complement prior research on the SNF sector in the U.S., which accounted for around $174 billion of spending in 2019 (Poisal et al. 2022). Given the importance of the sector and the fact that a growing set of hospitals and post-acute providers have common investors (Fowler et al. 2017), understanding the impact of organizational structure on treatment decisions and outcomes is relevant not only to competition policy but also to health care policy.

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

I. Background

I.A. 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. Once integrated, each firm faces an incentive to consider how its actions affect the profitability of the other firm(s). Vertical integration can create economies or diseconomies of scale and scope. More specifically, potential benefits of vertical integration include improved alignment of objectives across the merging 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" (Besanko et al. 2017). If realized, vertically 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 output, 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 an input rivals require. The downstream component of an integrated firm also has a reduced incentive to buy from upstream competitors, thereby potentially reducing competition in the upstream market as well.

The relationship between upstream and downstream healthcare providers differs from that reflected in the canonical value chain of production, in which the downstream firm purchases an input from the upstream firm. In our setting, the downstream firm (the SNF) receives referrals from the upstream firm (the hospital) but typically does not purchase this "input"; paying for referrals of publicly insured patients is prohibited by federal statutes. The effect of vertical integration on the incentives of the upstream and downstream divisions of an integrated entity is nonetheless similar in our setting and in the canonical model. Specifically, both the upstream and the downstream divisions of an integrated hospital-SNF face an incentive to consider how their strategic choices affect the profitability of the other division. In the canonical model, the upstream division of the integrated firm may have an incentive to "raise rivals' costs" – i.e., to make strategic choices that increase the profitability of the downstream division by reducing the competitive significance of downstream rivals. In this setting, the upstream division (the hospital) has an incentive to self-refer the most profitable patients to its downstream division (the SNF), which increases the profitability of the downstream division and reduces that of rivals.[4]

A specific concern that arises in the context of vertical provider mergers—and in other settings of information asymmetry regarding the value of a downstream product or service prescribed by an upstream seller—is the risk of inefficient "self-referrals" to co-owned providers. Such 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

[4] In the canonical value chain of production, the downstream division may have an "elimination of double marginalization" incentive to set a lower price than an unintegrated downstream firm if doing so increases profits of its upstream division. Because SNFs are such a small component of system revenues, we think this incentive is unlikely to be empirically detectable.

Baker, Bundorf, and Kessler (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, Wendling, and Wilson 2017; Capps, Dranove, and Ody 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, Ho, and Lee 2019; Easterbrook et al. 2019).[5] Finally, vertically integrated providers could raise rivals' costs or foreclose them from access to a critical input –profitable patients.

The literature on vertical provider mergers to date focuses on hospital-physician integration. Several studies find that hospital-physician integration raises healthcare prices and spending (e.g., Baker, Bundorf, and Kessler 2014; Capps, Dranove, and Ody 2018; Koch, Wendling, and Wilson 2017; McWilliams et al. 2018; Neprash et al. 2015; Robinson and Miller 2014). Studies examining the effect of hospital-physician integration on quality generally do not find evidence of improved clinical outcomes (e.g., Ho et al. 2019; Koch, Wendling, and Wilson 2018), although some find evidence of process and screening improvements (e.g., Carlin, Dowd, and Feldman 2015; Bishop et al. 2016). Konetzka, Stuart, and Werner (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 spending.

I.B. SNF-hospital Integration

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

[5] While the direction of the effect on pricing differs in Easterbrook et al. (2019) and Dafny, Ho, and Lee (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.

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 share of vertically integrated SNFs peaked in 1998 (Rahman, Norton, and Grabowski 2016), when Medicare adopted a site-neutral prospective payment system for SNFs that did not recognize cost differences between hospital-based and freestanding SNFs other than those related to case-mix and geography. Many hospitals subsequently closed or sold their SNFs during the next few decades. Notably, this trend was unaffected by the 2010 RUG update (see Figure A1). By 2012, the share of SNFs owned by hospitals stood at just over 14 percent.

During the study period, integrated SNFs had a higher overall rating, on average, than unintegrated SNFs on the SNF Five-Star Quality Rating System utilized by CMS (see Appendix A.1 and Table A1 for details). However, the overall rating is comprised of three components—health inspections, staffing, and quality measures—and integrated SNFs scored more highly on the first two and significantly lower on the third. Thus, while integrated SNFs may have been better resourced, this did not translate into improvements in measured patient outcomes.

Although formal ownership or "full integration" is relatively rare, more informal vertical affiliations exist between hospitals and SNFs. Konetzka, Stuart, and Werner (2018) note the presence of "informal integration" representing preferential relationships between providers without common legal ownership. Hospitals may form strong ties with SNFs through mechanisms such as shared electronic health records, sharing physicians or nurses to promote continuity, or preferentially referring patients. In a qualitative study of hospital-SNF collaborations, Rahman et al. (2018) distinguish strong ties by efforts of hospitals to establish SNF partners, initiatives to improve transitions to SNF, and having hospital staff at the SNF. In this study, we define integration as hospitals and SNFs with common ownership, but we also consider (and contrast) the behavior of hospitals with less formal collaborations, as proxied by relatively high referral rates to a specific SNF (i.e., the "most-preferred" among SNFs to which patients are discharged from a hospital).

As previously noted, there are several studies on the effects of care delivered by vertically integrated hospital-SNFs, including Doyle, Graves, and Gruber (2017), David, Rawley, and Polsky (2013), Rahman, Norton, and Grabowski (2016), and Konetzka, Stuart, and Werner

(2018). As compared to these prior studies, our analysis omits the effects of selection into inpatient treatment by an integrated hospital; we focus on the conditional effects of treatment in the downstream SNF facility.

I.C. Self-referrals

A small body of research confirms the popular wisdom that providers are more likely to refer patients to co-owned providers, e.g., physicians employed in hospital-owned practices are likelier to refer patients to the parent hospital system (Baker et al. 2016). 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 immediate family member) has a financial relationship with the entity performing the service."[6] 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. 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."[7] 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 2010 Affordable Care Act (ACA) 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.

Self-referrals are also important in the context of payment models that incentivize hospitals to constrain patients' post-discharge spending. The ACA encourages providers to form

[6] https://www.cms.gov/newsroom/fact-sheets/modernizing-and-clarifying-physician-self-referral-regulations-proposed-rule. See also 42 U.S.C. § 1320a-7b; 42 U.S.C. § 1395a.
[7] https://oig.hhs.gov/compliance/provider-compliance-training/files/StarkandAKSChartHandout508.pdf.

Accountable Care Organizations (ACOs) to coordinate patient care and collectively share responsibility for patient outcomes; there have now been several "generations" of ACO models and in 2020, nearly 14 million Medicare enrollees received care from an ACO.[8] Medicare has also implemented 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 through the Hospital Readmission Reduction Program, which reduces payments to hospitals with higher than predicted readmission rates. 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.

Prior evidence suggests that hospitals may also seek to benefit financially by self-referring based on patient profitability (e.g., Barro, Huckman, and Kessler 2006; Stearns et al. 2006; and Nakamura, Capps, and Dranove 2007). This raises the question: why don't hospitals with their own SNFs simply self-refer all or only the most profitable patients? The answer lies in demand- and supply-side constraints that impede hospital self-referrals to SNFs. On the supply side, many hospital-based SNFs operate close to capacity, making it challenging to only or always strategically self-refer patients. In addition, the Medicare program restricts hospitals' ability to steer patients to their own SNFs. While hospitals are required to present options for post-acute care to their patients, they are not permitted to recommend specific providers. However, hospital case managers, who are responsible for executing the discharge orders of physicians, can highlight which providers collaborate with the hospital, and in so doing may note some attributes they perceive as quality advantages, such as the sharing of electronic records and clinical staff.

Further, it is possible for case managers to target more profitable patients for their downstream nursing facility because patient profitability during a SNF stay is tied to the intensity of therapy the patient receives at the SNF. Certain conditions are more likely to require high rates of therapy, and certain patients are better able to tolerate the therapy, including those

[8] https://www.cms.gov/newsroom/press-releases/participation-continues-grow-cms-accountable-care-organization-initiatives-2024

without serious mental illness, Alzheimer's disease, obesity, and other comorbidities that can prevent delivery of high levels of therapy.

On the demand side, patient choice depends on various factors including past experience, expectations of quality of care, patient health status, and distance to the facility (Rahman, Norton, and Grabowski 2016). A recent qualitative study suggested proximity to home and prior experience with the facility most often influenced choice of SNF (Gadbois, Tyler, and Mor 2017).

I.D. The SNF Industry and the 2010 Change in Medicare Reimbursement of SNFs

SNFs provide patients with rehabilitative and nursing services following inpatient stays. Nearly three-quarters of SNFs are for-profit, and their total number has been relatively steady with 14,923 facilities in 2019, down only slightly from 15,178 in 2006. About 70 percent of care in SNFs is paid via public insurance programs, chiefly Medicaid– the U.S. public insurance program for low-income individuals– and Medicare– the program for the elderly and patients with disabilities. Medicare's SNF benefit is limited to short-term rehabilitation, whereas Medicaid also covers long-term care. While Medicare enrollees account for a smaller share of patient days than Medicaid, they account for a disproportionate share of revenues and have historically been profitable. The Medicare Payment Advisory Commission (MedPAC) estimates the margin for Medicare admissions to SNFs has exceeded 10 percent in every year from 2000 to 2020, inclusive (MedPAC 2022). Average margins for all non-Medicare admissions are far lower, yielding aggregate average margins ranging between -0.3 to 3.8 percent between 2001 and 2020. Thus, the Medicare program may have a disproportionate effect on the conduct of SNFs and their parent organizations.[9]

Between 1998 and 2019, traditional Medicare reimbursed most SNF care at a prospective daily rate.[10] 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 assessment tool

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[9] Sources for all reported SNF industry statistics are the annual MedPAC "Health Care Spending and the Medicare Program" databooks from 2016, 2018, and 2019, and the 2020 and 2021 annual MedPAC Report to Congress. 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.

[10] 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.

called the Minimum Data Set (MDS).[11] The MDS questionnaire addresses the degree to which the patient can perform several 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 to a RUG code; patients with similar therapy and nursing assistance needs are assigned to the same RUG code. Upcoding patients into more remunerative RUG codes is a well-documented practice (e.g., Bowblis and Brunt 2014; Levinson 2010). Our interest is in how patient profitability impacts self-referrals and the quality of care, so our study design isolates changes in profitability not related to upcoding.

We isolate changes in profitability that resulted from changes 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.[12] First, CMS altered the MDS questionnaire used to assign patients to a RUG. The new assessment was backward-compatible but not forward-compatible. That is, with the RUG-IV questionnaire, one can determine a patient's RUG-III code, but the converse is not true for the RUG-III questionnaire. 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 RUG codes from 53 to 66. These changes collectively generated 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 *relative* changes in prices from the FY2011 update persisted (MedPAC 2015).

II. Data

[11] All patients admitted to a SNF receive a "5-day assessment," which determines reimbursement for days 1 through 14 of the patient's 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.

[12] "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).

II.A. Medicare Data

Our main source of data is the 100 percent sample of Medicare claims from September 2007 to December 2012 (Centers for Medicare and Medicaid Services, 2007–2012b, 2007–2012c). We subdivide the data into hospital discharges, SNF discharges, and all other claims. Although our focus is on discharges to SNFs following hospital stays, we also make use of other claims to construct measures of outcomes within 90 days of a hospital discharge.

II.A.1. Inpatient Discharge Data

We match the Medicare hospital discharge claims to hospital-year characteristics obtained from the Hospital Cost Reports, collected by CMS (Centers for Medicare and Medicaid Services, 2007–2012a, n.d.). We set aside the inpatient data from the last quarter of 2007 (October to December) and the first quarter of 2008 (January to March) to calculate several "initial state" variables used in the analyses; we refer to this data as the "training sample" (Centers for Medicare and Medicaid Services 2007–2012c). We limit the sample during the study period (2008Q2 to 2012Q4) to discharges from GACs with inpatient claims in each year from 2008 to 2012, inclusive. We identify those hospitals that own at least one SNF subprovider in all years from 2008 through 2012; these are "integrated hospitals." Hospitals that never own a SNF subprovider between 2008 and 2012 are labeled "unintegrated hospitals." We exclude discharges from hospitals with changes in SNF ownership during this period; these account for just 8 percent of the 51 million discharges from GACs during the study period. Table A2 summarizes the effect of each sample restriction on the number of claims and hospitals.

II.A.2. SNF Claims Data

We use Medicare SNF claims data to link SNF stays to inpatient discharges (Centers for Medicare and Medicaid Services 2007–2012c). The SNF claims data include the dates of admission and discharge from the SNF, the patient's RUG code (which may vary during the stay), 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). We define "referrals" to SNFs as admissions commencing within 10 days of an inpatient hospital discharge. In most analyses, we restrict the inpatient claims sample to the 8.9 million inpatient stays that are followed by a SNF referral. We also calculate an average daily reimbursement rate for each SNF visit, which we refer to as *price*. Further details are in Appendix A.2.

To construct our price shock instrument, we need a mapping of patient assessments to both RUG-III and RUG-IV codes used for reimbursement. The patient assessment data and corresponding RUG codes appear in a separate Medicare file called the SNF Minimum Data Set (MDS) (Centers for Medicare and Medicaid Services 2011). We use MDS data from 2011Q1-2011Q3, during which both the old and new RUG codes are reported (for further detail, see Appendix B), to link RUG-III to RUG-IV codes. We use this data as an input in constructing our price instrument, which is described in greater detail in Section II.B below.

II.A.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 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 (Centers for Medicare and Medicaid Services 2007–2012c).[13] We use the Medicare Master Beneficiary Summary File to obtain patient demographic information, including age, race, sex, and date of death, where applicable (Centers for Medicare and Medicaid Services 2007–2012a).

II.B. 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

[13] 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 A9, we show that results are similar for this subset and the 100 percent sample with carrier and DME costs excluded.

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.[14] In this section, we explain how we construct a patient-level measure of the change in reimbursement, which we call *predΔprice*.

A key concern is that SNFs have a financial incentive to distort patient assessments to maximize reimbursement, and the reform impacted these incentives. Thus, we do not rely on characteristics reported on SNF assessments or SNF claims to determine the magnitude of the price shock or to track similar patients over time. Instead, we leverage the fact that effectively all Medicare-reimbursed SNF stays follow an inpatient stay, and inpatient claims contain detailed patient demographics and diagnoses that do not determine SNF reimbursements but are correlated or predictive of those reimbursements. Hospitals do not have a financial incentive to distort the patient characteristics reported on an inpatient claim in response to the reform, as inpatient data does not affect SNF reimbursement. We use the observed association between inpatient data and subsequent RUG codes as an input to construct the instrument, i.e., the mechanical effect of the update on SNF reimbursement. Our procedure is similar in spirit to a simulated instrument procedure (as in Currie and Gruber (1996)), although in this setting we use a pre-reform "mapping" from inpatient characteristics to RUG-III codes—and then RUG-III codes to RUG IV codes—and hold this constant over time, while allowing the set of discharges to change, whereas Currie and Gruber (1996) fix the set of individuals and allow the policies to vary across states and over time.

We construct the instrument in two steps. First, we calculate the "mechanical" price change associated with the update (i.e., untainted by potential changes in SNF behavior) using the correspondence of each RUG-III code to RUG-IV codes and CMS' RUG-III and RUG-IV reimbursement rate tables (Centers for Medicare and Medicaid Services 2009, 2010). Through the MDS data wherein both RUG-III codes and RUG-IV codes are recorded for patients, we obtain the probability that a patient with RUG-III code j would be categorized as RUG-IV code k. These probabilities combined with the FY2010 RUG-III and FY2011 RUG-IV reimbursement rates provide the anticipated price increase from the reform for each j.

[14] 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.

Next, we link the RUG-III code price shocks to patients in a set-aside patient sample and use the resulting dataset to predict the price change for patients in the broader estimation sample. We assign the "mechanical" price changes to patients with SNF referrals from October 2007 to March 2008 (the training sample) based on their RUG-III codes. We then regress the price changes on a set of patient inpatient diagnostic and demographic information (e.g., age, race, inpatient diagnosis) (Centers for Medicare and Medicaid Services and Agency for Healthcare Research and Quality 2008). The resulting coefficients flexibly capture the correlation between patient characteristics and the need for nursing and rehabilitation services. Finally, we use the estimated parameters to predict the "mechanical" price change for each patient in the estimation sample (i.e., all inpatient stays between 2008Q2 to 2012Q4). We call this variable (our price instrument) *predΔprice*; further details on this process and explanatory examples are presented in Appendix B. This strategy leverages reimbursement changes associated with patient characteristics that are unlikely to be altered in response to the shock, e.g. *predΔprice* is different for females hospitalized for stroke and males hospitalized for joint replacements.

II.C. 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., whether the patient has been self-referred by an integrated hospital). We also calculate 90-day total patient spending incurred after the inpatient discharge. We take the natural logarithm and winsorize at the 1^{st} and 99^{th} percentiles for the relevant quarter. We construct two patient-level, clinical outcome measures: mortality and readmission, both within 90 days of the inpatient discharge. Mortality is determined using date of death reported in the Medicare Master Beneficiary Summary and readmission is determined using the inpatient claims data.

Finally, we develop four 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 other three controls are constructed analogously; *propensity for SNF referral* uses an indicator variable for SNF referral after hospital discharge, while *mortality risk* and *readmission risk* use indicator variables for death or readmission within 90 days of hospital discharge, respectively. Each composite, patient-level control is included in the model that uses the corresponding outcome as the dependent variable. Further details are in Appendix A.3.

II.D. 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. Statistics are displayed separately for discharges from integrated and unintegrated hospitals. Panel A shows the propensity for a SNF referral is slightly higher among discharges from integrated hospitals (21 percent) versus unintegrated hospitals (18 percent). Panel B shows that nearly 1 in 3 patients discharged to a SNF by an integrated hospital is self-referred (i.e., goes to the discharging hospital's SNF). There are very modest differences in the demographic characteristics of patients discharged to a SNF from the two categories of hospitals, although due to the large sample size the differences are all statistically distinguishable from zero.

Turning to hospital-level descriptive statistics, which are presented in Table A3 and Figure A2, just over one-third of the sample (921 of 2,646 hospitals) is integrated with a SNF. Relative to unintegrated hospitals, integrated hospitals have fewer beds, are less likely to be for-profit, are more likely to be in the South, and are in zip codes with lower median household income. Integrated hospitals also tend to have lower average occupancy rates and lower net operating margins, defined as net patient revenue less reported expenses from providing services (and averaged over 2005-2007 for each hospital). Our models incorporate hospital fixed effects to control for these observed differences across hospitals in each group.

Figure 1 displays the distribution of *predΔprice* for patients discharged from GACs during the study period. All patients had a positive *predΔprice*, with a range of 9.5 percent to 20 percent and an average of 14.4 percent. The distribution of *predΔprice* is highly similar before and after the RUG update (Figure A3), indicating any changes in patient composition during this period were uncorrelated with *predΔprice*.[15] To better understand the correlates of *predΔprice*, Table A4 presents summary statistics separately for patients with above- and below-median values of *predΔprice*. Patients with *predΔprice* above the median are three times as likely to be

[15] The Kullback-Leibler divergence between a 100-bin histogram of *predΔprice* before and after the RUG update is 0.0001726.

dually eligible for Medicaid and more than twice as likely to be Black.[16] However, variation in *predΔprice* is not captured by a unidimensional measure of patient health such as mortality risk, nor by condition group. For example, patients with above-median values of *predΔprice* have a 31 percent *lower* Charlson comorbidity index (i.e., *fewer* comorbidities) than do patients with below-median values of *predΔprice*. In addition, there is no pattern in terms of diagnosis categories (Table A5). The price shock increased the relative profitability of patients diagnosed with kidney infections, hip and femur procedures, or stroke, and decreased the relative profitability of patients hospitalized for major joint replacement, heart failure, or pneumonia. Even diagnoses that are categorically similar have different *predΔprice* variation. For example, patients with hip procedures *except* major hip replacement are likely to have high *predΔprice*. Similarly, pneumonia patients can expect below-median *predΔprice* while those with other respiratory infections typically have above-median *predΔprice*.

III. Estimation

III.A. First-Stage Analysis

We begin by exploring the validity of our instrument for SNF price. We estimate the following equation using the sample of patients discharged from a hospital to a SNF:

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

where *i* indexes individuals, *t* indexes the quarter in which an individual was discharged from the hospital, *h*(*i*) denotes the discharging hospital, and *predΔprice* is the predicted price shock for individual *i*. *t* is centered around the last quarter before the SNF RUG payment update, that is, *t*=0 corresponds to 2010Q3. 2010Q3 is a transition quarter because some patients discharged from hospitals during it had sufficiently long SNF stays that their SNF care was reimbursed

[16] Table A4 shows that patients with high *predΔprice* are ex-ante less likely to be self-referred than patients with low *predΔprice*. This result may reflect several factors. First, price is not the only factor which drives self-referrals. Differences in the mix of demographics and DRG codes for patients with low vs. high *predΔprice* may independently affect the propensity for self-referral of the two different groups. Second, even if hospitals *only* consider patient profitability when self-referring, *predΔprice* reflects the expected change in profitability, not the absolute level. To the extent that CMS' objective is to equalize patient profitability over time, then patients that were ex-ante less profitable would have been likelier to experience larger increases in reimbursements (higher *predΔprice*).

under both RUG systems. $\mathbb{1}_t$ represents a set of indicator variables for the 19 quarters in our estimation period. The coefficients of interest are represented by β_t^2, which captures the evolution of the impact of *predΔprice* on actual price. To achieve identification, we restrict β_{-1}^2 to 0. We are interested in estimates for β_t^2 during the post-update period, $t \geq 1$.

Equation (1) also includes hospital-quarter fixed effects ($\beta_{h(i)t}^0$) and hospital-specific coefficients on *predΔprice* ($\beta_{h(i)}^1$). The rationale can be made transparent by considering (as a thought exercise) a binary version of the instrument, i.e., high or low *predΔprice*. Our objective is to compare outcomes for patients with high versus low *predΔprice* before and after the RUG update. We must therefore control for time-period effects (quarter fixed effects) and "treatment group" effects (a high *predΔprice* indicator in this thought exercise). However, this specification would ignore the role of hospitals, which substantially influence the SNF referral decision for a patient; changes in patient composition and practice styles over time across and within hospitals could bias our estimate. Therefore, we add interactions between the time and treatment group effects with hospital fixed effects.

Thus, the hospital-quarter fixed effects control for unobservable, time-varying factors potentially correlated with referral decisions and with outcomes, such as hospital-specific trends in discharge to post-acute care or changes in hospital quality. The hospital-specific coefficient on *predΔprice* (or in the thought experiment, the indicator for high *predΔprice*) accounts for the possibility that some hospitals may be differentially better or worse at treating patients with different values of *predΔprice*. If there are changes in the distribution of patients across hospitals post-reform, excluding these interactions could bias the estimated effect of the reform on the outcome measures. We cluster standard errors by *predΔprice* such that each cluster represents a set of individuals with the same value of *predΔprice.* We discuss alternative clustering approaches in Section IV.E.

Figure 2 graphs the estimates of β_t^2 from equation (1), depicting the relationship between *predΔprice* and ln(*price*) in each quarter relative to *t=-1*. The coefficients are near zero before the price shock, increase to greater than one in the first full quarter under the RUG update (further discussion of this magnitude appears below), and then decrease to around one. The estimates of β_1^2 and β_9^2 from equation (1) are statistically distinguishable at p<0.001. The small decrease is the result of CMS's adjustment of SNF prices in FY2012, described previously; these adjustments slightly reduce the boon to SNF admissions benefiting more from the initial update, but the association between actual and predicted price remains quite large (Centers for Medicare and Medicaid Services 2011a).

We also estimate a parsimonious version of equation (1) using a pooled post-period:

$$\begin{aligned} ln(price_{it}) = \beta^{0}_{h(i)t} + \beta^{1}_{h(i)} \cdot pred\Delta price_i + \beta^2 \cdot quarter_t \cdot pred\Delta price_i \\ + \beta^3 \cdot post_t \cdot pred\Delta price_i + \beta^4 \cdot post_t \cdot quarter_t \cdot pred\Delta price_i \\ + \beta^5 \cdot \mathbb{1}(quarter = 0)_t \cdot pred\Delta price_i + \varepsilon_{it}, \end{aligned} \tag{2}$$

where *quarter* is the quarter of patient discharge, centered around $t = 0$ and ranging from -9 to 9. *Post* is an indicator that is equal to 1 for $t > 0$. We include a separate coefficient capturing the impact of the price shock in the transition quarter as some patients discharged during this period had their SNF care partially reimbursed under the RUG-IV system. 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∆price*.

Barring a shock-induced change in SNF referral patterns and measurement error, β^3 should be close to 1. The actual point estimate is 1.24 (standard error of 0.042), and statistically significantly greater than 1 (Table 2, column (1)). The coefficient of interest falls below 1 upon the addition of SNF-quarter fixed effects (see column (2) of Table A6 and Figure A4). Thus, changes in SNFs to which patients are referred magnify the effect of the reimbursement shock on total spending (i.e., the "price" of a SNF visit). [17]

III.B. The Impact of Price on Self-Referral

Next, we assess how changes in relative 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-referral,* which takes on a value of 1 if a patient is self-referred:

$$\textit{self-referral}_{it} = \beta^{0}_{h(i)t} + \beta^{1}_{h(i)} \cdot pred\Delta price_i + \sum_{q\in[-9,9]} \beta^2_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i + \varepsilon_{it}. \tag{3}$$

We first perform this reduced-form regression on the sample of discharges from an integrated hospital to any SNF ("SNF discharges"); the estimates of β^2_t are graphed in Figure 3. There is no

[17] Note that outcomes of interest include whether the patient is self-referred to the hospital's owned SNF and the effect of self-referrals on outcomes. We do not include SNF-quarter or SNF- *pred∆price* controls because such controls would condition on an outcome resulting from the price shock.

apparent pre-period trend, i.e., there is no indication that patients with higher values of *predΔprice* experience significant changes over time in the rate at which they are self-referred in the 2 years leading up to the price shock, except for a temporary increase 2 quarters before the price change and a pooled test of the pre-period coefficients fails to reject the null that they are equal to zero at p=0.22.

We next estimate a model that pools the post-period, while allowing for differential trends and main effects of *predΔprice* during the pre- and post-periods, i.e.:

$$\begin{aligned} \textit{self-referral}_{it} = {} & \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \beta^2 \cdot quarter_t \cdot pred\Delta price_i \\ & + \beta^3 \cdot post_t \cdot pred\Delta price_i + \beta^4 \cdot post_t \cdot quarter_t \cdot pred\Delta price_i \\ & + \beta^5 \cdot \mathbb{1}(quarter = 0)_t \cdot pred\Delta price_i + \varepsilon_{it}. \end{aligned} \tag{4}$$

As before, we estimate both the short-run or "level" effect of the price shock (β^3) and the longer-term change in the trend of self-referrals (β^4). Given the complexity of the reimbursement change, it may take some time for hospitals (and perhaps their consultants) to fully realize and then act upon the changes. In addition, SNFs may need to modify practices and services to accommodate the change in patient composition arising due to a change in self-referrals.

The results are displayed in column (2) of Table 2. Consistent with the pattern of coefficients from Figure 3, there are shifts in both the level and trend of the relationship between self-referral rates and *predΔprice* during the post-period. To ease interpretation, the table includes an estimate for the combined effect in the final quarter of our analysis (i.e., the fourth quarter of 2012) based on the coefficient estimates. The magnitude of this effect is large: by the end of 2012, a one percentage point change in predicted price increases a hospital's propensity to self-refer a patient by 0.63 percentage points.[18]

Because these estimates rely on a predicted independent variable, *predΔprice* – which incorporates some error– the standard errors in column (2) of Table 2 are understated. To assess the magnitude of this bias, we bootstrap equation (4) using multiple estimates of *predΔprice* and report the bootstrapped confidence intervals in Table A6 (see Appendix C for details). The

[18] We also estimate an alternative version of equation (3) which utilizes within hospital-DRG variation in *predΔprice* by fully interacting the fixed effects in the specification (i.e., hospital fixed effects and hospital *predΔprice* interactions) with DRG fixed effects. This specification yields a slightly larger, statistically significant estimate of the effect of *predΔprice* in 2012Q4, but the estimate is not statistically distinguishable from that produced by equation (3) and leverages only a small amount of the variation generated by patient characteristics. We therefore opt to include just hospital-quarter and hospital-*predΔprice* fixed effects in our main specification.

confidence intervals are slightly larger after the bootstrapping procedure, but we still reject the null hypothesis of no self-referral effect at $\alpha<0.01$.

A change in self-referral rates could be due to an increase in the rate of referral to any SNF, an increase in the rate of self-referral conditional on a referral, or some combination of the two. To disentangle the potential sources of the observed increase in self-referral correlated with *predΔprice*, we estimate models using the binary outcome variable *SNF referral*, which takes a value of 1 if a patient is referred to any SNF and using the sample of all hospital discharges from integrated hospitals, rather than just those discharged to SNFs. In these models, we add the previously described variable, *propensity for SNF referral*, which serves as a parsimonious control for patient characteristics that are correlated with both *predΔprice* and *SNF referral*. This control was not necessary in equation (4), which was estimated using the sample of patients referred to SNFs. Although including *propensity for SNF referral* improves the precision of our estimates in models of *SNF referral*, the point estimates are unaffected by its inclusion.

We first estimate a version of the model including quarterly interactions with *predΔprice*:

$$\begin{aligned} \text{(5)} \quad SNF\,referral_{it} = {} & \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \sum_{q\in[-9,9]} \beta^2_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i \\ & + \alpha \cdot propensity\ for\ SNF\ referral_i + \varepsilon_{it}. \end{aligned}$$

The results, plotted in Figure 4, suggest no relationship between the propensity for any SNF referral and *predΔprice*.[19] However, the results of the pooled post-period specification,

$$\begin{aligned} \text{(6)} \quad SNF\,referral_{it} = {} & \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \beta^2 \cdot quarter_t \cdot pred\Delta price_i \\ & + \beta^3 \cdot post_t \cdot pred\Delta price_i + \beta^4 \cdot post_t \cdot quarter_t \cdot pred\Delta price_i \\ & + \beta^5 \cdot \mathbb{1}(quarter = 0)_t \cdot pred\Delta price_i \\ & + \alpha \cdot propensity\ for\ SNF\ referral_i + \varepsilon_{it}, \end{aligned}$$

reported in column (1) of Table 3, reveal a small, negative, and statistically significant relationship between the likelihood of any SNF referral and *predΔprice* during the post period. That is, discharges with higher *predΔprice* are slightly *less* likely to be referred to any SNF post-discharge. We therefore re-estimate equation (4) using the full sample of hospital discharges and

[19] While the effect of *predΔprice* on SNF referral appears to be null, this could be specific to integrated hospitals. We examine whether the effect of *predΔprice* on SNF referral is different for integrated hospitals and unintegrated hospitals by adding unintegrated hospitals to the sample and including interaction terms between integration status and the leads and lags of *predΔprice*. Figure A5 plots the coefficient estimates separately for integrated and unintegrated hospitals; both time series are similar and none of the interactions terms in the pooled regression is statistically significant at $p<0.35$.

including *propensity for SNF referral* as a control variable. The results, displayed in column (2), indicate that patients with a larger *predΔprice* are likelier to be self-referred after the shock. This result shows that the increase in self-referral conditional on any SNF referral (column (2) of Table 2) outweighs the decrease in the rate of referrals (column (1) of Table 3).[20]

Last, we present 2SLS estimates of the effect of price on self-referral, returning to the sample of patients referred to a SNF, using *post · predΔprice* and *post · quarter · predΔprice* as instruments for *ln(price)* and *ln(price) · quarter*. Using the resulting coefficient estimates (column (3)) and the pre-period probability of self-referral of 33.2 percentage points, we calculate a self-referral elasticity of 1.8, i.e. a one percent increase in SNF price (instrumented by *predΔprice*) results in a 1.8 percent increase in the self-referral rate.

Next, we consider whether referrals by unintegrated hospitals to their "most-preferred" SNF are also affected by the changes in *predΔprice***.** Evidence of a similar response would suggest that looser forms of vertical affiliation lead to similar conduct, i.e., that hospitals attempt to improve the profitability of partners regardless of whether they are co-owned. Alternatively, this analysis could be viewed as a placebo test because the unintegrated hospital realizes no direct financial benefit from directing more profitable patients to their most-preferred SNFs, particularly during the study period which precedes the ACA and therefore ACOs.

We define the "most-preferred" SNF as the SNF receiving the greatest share of a hospital's SNF referrals during the pre-period, 2008Q2-2010Q3. Summary statistics for the distribution of "most-preferred" SNF share are provided in Table A8. They show that integrated hospitals rely more heavily than unintegrated hospitals on their most-preferred SNF, and this is especially true when the most preferred SNF is a SNF they own. Note that integrated hospitals' most preferred SNF is not always a SNF that is owned by that hospital, although this is usually the case (i.e., occurs for 63 percent of hospitals, accounting for 73 percent of SNF referrals).

We begin by re-estimating equation (4) after limiting the original sample (SNF discharges from integrated hospitals) to SNF discharges from integrated hospitals whose most-preferred SNF is co-owned. The results, reported in column (1) of Table 4, are similar, if slightly larger, than those in column (2) of Table 2. To study whether self-referral patterns change

[20] The net effect corresponds to a self-referral elasticity of 1.7, in line with the computed elasticity above. A percentage point change in price leads to an increase of 0.11 percentage points in *self-referral*. Given the average unconditional self-referral rate of .068, this represents an increase of 1.68 percent.

similarly for unintegrated hospitals with looser vertical ties, we take the set of integrated hospitals from column (1) and match them to a comparison group of unintegrated hospitals. We drop a small number of integrated hospitals without matched comparison hospitals. Additional details on the matching procedure can be found in Appendix D.

Columns (2) and (3) of Table 4 contain coefficient estimates from separately estimating equation (4) for the treatment and matched control samples, substituting the dependent variable *self-referral* with *most-preferred-referral,* an indicator variable taking a value of 1 when a patient is referred to a hospital's most-preferred SNF. We find a statistically significant response to the price shocks by integrated hospitals (column (2)), but a smaller, statistically insignificant response by unintegrated hospitals (column (3)).

III.C. 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. The estimation sample for this analysis includes SNF admissions from both integrated and unintegrated hospitals because the RUG update not only affected the likelihood of self-referral, but it also affected the prices directly paid to SNFs; each of these changes could independently affect outcomes. Patients admitted to SNFs from unintegrated hospitals are subject to only the "price effect" of the RUG update, whereas patients admitted to SNFs from integrated hospitals are subject to both the "price effect" and the "self-referral" effect.

We again begin with a reduced-form specification that allows for quarterly interactions with *predΔprice*:

$$\begin{aligned} Y_{it} = \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \sum_{q \in [-9,9]} \beta^2_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i \\ + \sum_{q \in [-9,9]} \beta^3_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i \cdot integrated_{h(i)} + \alpha \cdot X_i + \varepsilon_{it}, \end{aligned} \tag{7}$$

where Y represents *mortality*, *readmission*, and ln(*spending*), as previously defined. β^2_t reflects changes over time in the relationship between outcomes and the instrument for discharges from unintegrated hospitals, and β^3_t reflects any differential changes among discharges from integrated hospitals. X_i represents a patient-level risk adjustment factor, which varies for each outcome. Appendix A.3 contains additional details; results without the risk adjustment factors are similar across all specifications. 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.

Figure 5 depicts the impact of *predΔprice* on outcomes separately for unintegrated hospitals and integrated hospitals. While visual inspection of Figure 5 does not suggest differences in pre-reform trends between the two groups for any of the three outcome measures, regression results obtained from models replacing the quarterly interactions with a pooled post-period indicator and testing the differences in levels and trends between the two reveal show a statistically significant difference in the pre-reform trend for one of the outcome measures, *readmission* (see Table A10). We therefore formally estimate the impact of self-referrals on patient outcomes in a 2SLS framework only for *mortality* and ln(*spending*). Neither of the 2SLS estimates is statistically distinguishable from zero, and the confidence intervals are wide. Thus, while we do not find evidence that outcomes are impacted by self-referral, we are unable to rule out economically meaningful increases or decreases in these outcomes. Additional discussion and tables of these results are in Appendix E. Given that integrated SNFs do not appear to have higher quality in terms of patient outcome measures as discussed in Section I.C, it is perhaps unsurprising that we fail to find significant outcome effects of self-referral.

IV. Heterogeneity, Robustness, and Extensions

IV.A. 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 *predΔprice* 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. Additional details on these measures are in Appendix A.4. For each characteristic, we report the combined effect of the treatment in the final quarter in Table A11. We find that no characteristic is significantly associated with a heterogenous response at the 5-percent level. 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 *predΔprice* in 2012Q4 by more than 50 percent. Thus, hospitals under more pressure to discharge patients are less responsive to the change in incentives to self-refer.

IV.B. Potential Hospital Behavioral Responses

In conducting our main analyses, we calculate *predΔprice* 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 behavior, could yield biased estimates of the impact of self-referral on outcomes. Our estimation strategy thus relies on the fact that hospitals lack an incentive to manipulate *inpatient* diagnoses based on the SNF reimbursement rate because inpatient diagnoses do not affect SNF reimbursement rates, notwithstanding the fact that we use them to *predict* SNF reimbursement rates. As a check to confirm that hospitals did not respond to the price shock by systematically changing diagnosis codes (DRGs) to assign more patients to DRGs with positive price shocks, we perform an analysis to evaluate whether hospitals alter their admissions or coding following the update in ways that are correlated with *predΔprice*. To that end, we construct two alternative measures of *predΔprice* at the DRG-level, *predΔprice'* and *predΔprice_avg*. *predΔprice'* is time-invariant and calculated similarly to *predΔprice* but only using a patient's DRG; details on its construction in Appendix B.4. *predΔprice_avg* is the average *predΔprice* for a hospital-DRG-quarter triad. While *predΔprice_avg* corresponds more closely to the variation in *predΔprice* used in our main analysis, such a time-varying measure could be biased if hospitals are engaging in upcoding behavior following the price shock. Next, we create counts for the number of patients corresponding to each hospital-DRG-quarter triad (*PatientPop*). Finally, we estimate the association between quarterly values of *PatientPop* and each of our newly constructed measures, controlling for hospital-quarter fixed effects and hospital-DRG fixed effects and clustering standard errors at the DRG-level. We find no systematic change in the relationship between *PatientPop* and either alternative measure of *predΔprice* around the time of the RUG update (Figure A7).

IV.C. Robustness to the Hospital Readmissions Reduction Program

In 2010, the ACA 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 DRGs targeted by the HRRP have systematically higher or lower values of *predΔprice* 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 (Centers for Medicare and Medicaid Services 2014). We find the estimated relationship between *predΔprice* and self-referrals is relatively unchanged (see Figure A7). We also find no statistically significant differences in coefficients when estimating equation (4) for the full sample versus the HRRP-excluded sample (see Appendix F).

IV.D. Sensitivity of Results to Alternative Combinations of Controls

The control variables in our specifications include hospital and time fixed effects, as well as outcome and patient-specific predictors (e.g., readmission risk or predicted spending). We utilize the raw patient characteristics to construct *predΔprice*, our primary independent variable of interest. This approach precludes us from incorporating these characteristics directly into our analysis as controls, raising the concern that changes in patient composition or in outcomes over time for patients with specific characteristics may affect the results. We address these potential concerns in three ways.

First, we calculate a risk-adjustment score for self-referral, *self-referral propensity*, which is constructed in a similar manner as the other risk-adjustment measures. We then estimate our main specification (represented by equation (1)) using this measure as the dependent variable. The results, presented in Figure A8, show no changes in the relationship between *predΔprice* and *self-referral propensity* concurrent with the price shock. Furthermore, controlling for *self-referral propensity* in our main specification has minimal impact on our estimates.

Next, we assess the sensitivity of our findings to observable but omitted individual-level characteristics by considering six additional sets of controls: (1) distance-to-facility measures, (2) income measures (based on median income in the individual's zip code), (3) variables reflecting the individual's health risk, (4) Medicare plan characteristics, (5) prior-year facility visits, and (6) discharge day/month; each set of controls is described in detail in Appendix F.1. We interact all controls with quarter fixed effects to allow for time-varying relationships between outcome measures and the controls. To conduct the sensitivity analysis, we follow the methodology of

Card, Fenizia, and Silver (2023). We repeatedly sample different permutations of our additional sets of controls to add to our principal model. Details of this approach and a plot of the resulting estimates for the effect of *predΔprice* in 2012Q4 are presented in Appendix F.2 and Figure A9, respectively. The estimated effect is modestly attenuated with the addition of controls and remains statistically significant for all permutations. The estimated self-referral elasticity with all sets of controls included is 1.4 as compared to 1.9 in our baseline specification with no added controls.

Finally, our main result showing self-referral decisions are impacted by changes in patient profitability relies on within-hospital comparisons across patients. This estimate will be biased if *predΔprice* is associated with omitted factors also correlated with the propensity to self-refer. Earlier, we addressed this concern by confirming the absence of pre-trends, i.e., we find no evidence that patients with higher *predΔprice* are likelier to be self-referred *before* the RUG update. Here, we discuss results obtained when adding a control group of hospitals, specifically critical access hospitals ("CAHs") that own a so-called "swing-bed SNF," i.e., integrated CAHs. Swing-bed SNFs are located within a hospital and are comprised of beds that can be used either for inpatient or for SNF care. CMS designates certain hospitals that meet requirements regarding size, distance to another hospital, and services provided as CAHs. Crucially, Medicare reimburses for swing-bed SNFs within CAHs on a cost-plus basis, and therefore these SNFs were not subject to the RUG update.

To determine whether the differences in self-referral patterns between integrated GAC hospitals (i.e., the sample in column (1) of Table 2, the treatment group) and integrated CAHs (the control group) are statistically distinguishable, we pool discharges to SNFs from both groups of hospitals and estimate a variant of equation (3), which includes additional interactions for patients in the treatment group:

$$\begin{aligned} self\text{-}referral_{it} &= \beta^0_{h(i)t} + \beta^1_{h(i)} \cdot pred\Delta price_i + \sum_{q\in[-9,9]} \beta^2_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i \\ &+ \left[\sum_{q\in[-9,9]} \beta^3_t \cdot \mathbb{1}_{t=q} \cdot pred\Delta price_i\right] \times GAC_{h(i)} + \varepsilon_{it} \end{aligned} \tag{8}$$

where $GAC_{h(i)}$ takes a value of 1 if the patient is discharged to a SNF from an integrated GAC hospital and 0 if the patient is discharged to a SNF from an integrated CAH. The coefficients of interest are represented by β_t^3, which capture the extent to which patients with higher values of *predΔprice* are likelier to be referred to a SNF owned by their discharging hospital following the price shock if the hospital is an integrated GAC rather than an integrated CAH. We start by depicting the time-varying relationship between *predΔprice* and *self-referral* separately for integrated GACs ($\hat{\beta}^2 + \hat{\beta}^3$) and integrated CAHs ($\hat{\beta}^2$) in Figure A10. There is no apparent difference in the pre-period trends for the two groups, but integrated GACs exhibit a surge in the coefficient of interest during the post-shock period. Figure A11 plots the time series for $\hat{\beta}^3$, which confirms that by the end of our estimation period, GACs differentially self-refer patients with higher values of *predΔprice* as compared to CAHs. A Wald test rejects the null that all $\hat{\beta}^3$ coefficients in the post-period are indistinguishable from 0 at the 1% significance level. Finally, comparing the two groups in the parsimonious version of equation (8) which permits different pre-period trends and pooled post-period level and trend responses confirms no difference in pre-period trends and a statistically different post-period trend.

IV.E. Robustness to Alternative Clustering of Standard Errors

Last, we explore whether the reduced-form results are robust to alternative clustering of standard errors. We consider four alternative clustering approaches: clustering by hospital; clustering by hospital-quarter; non-nested, two-way clustering by *predΔprice* and hospital; and clustering by *predΔprice* bins of varying size. The results displayed in Table A12 show that the standard errors are similar across these methods and our key finding—that expected patient profitability affects the likelihood of self-referral—is always statistically significant at the 1% level.

V. Discussion and Conclusions

V.A. 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 1.8. 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.[21]

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 *predΔprice* to their own SNFs during the post-shock period, holding their total SNF admissions constant (see Appendix A.5 for details). We calculate that vertically integrated hospitals realized 68 percent of this theoretical maximum as of the fourth quarter of 2012. This estimate suggests a sizeable cherry-picking response.

Third, we find that the total increase in payments captured by vertically integrated hospital-SNF entities because 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.[22] 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).

V.B. Conclusions

In the wake of a 2010 change in Medicare reimbursement for SNFs, we find integrated systems were likelier to discharge patients who became relatively more profitable to their own SNFs, thereby disadvantaging independent SNFs. We do not find evidence that self-referral leads to improvements in 90-day mortality or reductions in Medicare spending, although we cannot rule out such effects due to large confidence intervals. Together, these facts suggest that

[21] We estimate this elasticity using figures presented in Rahman, Norton, and Grabowski (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.

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

vertically integrated healthcare providers can successfully refer more profitable patients to their internal subsidiaries, potentially foreclosing rivals. Notably, few SNF acquisitions have been reviewed *ex ante*; likely in part because these acquisitions have rarely exceeded the reporting thresholds to the federal antitrust agencies.[23]

A small number of states now require public reporting of healthcare transactions, regardless of size; based on prior research on horizontal mergers, more transparency may deter anticompetitive transactions going forward (Wollmann 2019). More generally, evidence of potential foreclosure such as that documented in this study, along with the revised *Merger Guidelines* and a publicly announced study by the FTC on physician group and healthcare facility mergers, suggest vertical provider transactions might receive greater scrutiny going forward.

[23] Only 9 acquisitions of nursing home facilities were reported to the federal antitrust authorities during FY2008-2012, inclusive. By comparison, 129 hospital acquisitions were reported during the same period. Source: https://www.ftc.gov/policy/reports/annual-competition-reports

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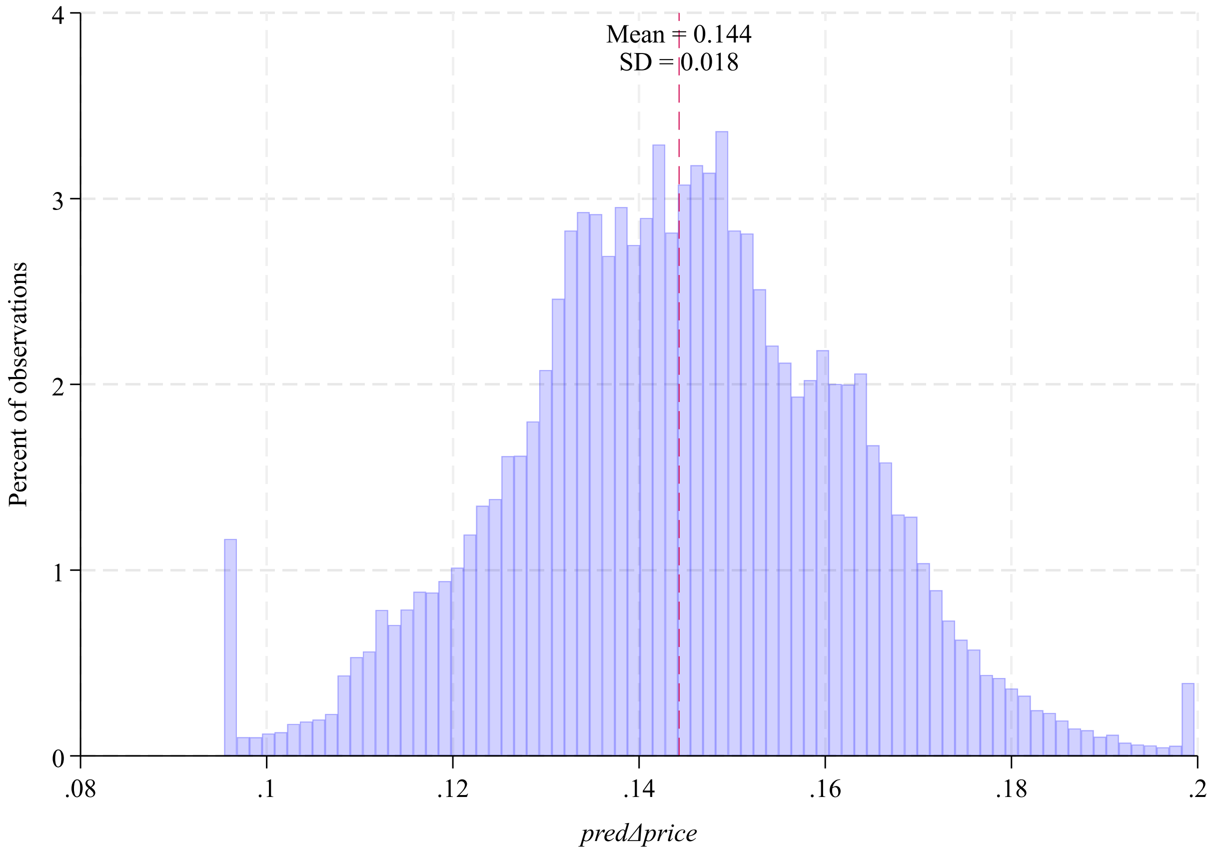
Table 1: Patient Characteristics by Sample Group

	(1) Integrated hospitals	(2) Unintegrated hospitals	(1) - (2) Difference
Panel A: All inpatient discharges			
Referral to any SNF	0.212	0.184	0.028
	[0.409]	[0.388]	
Hospital stay >=3 days	0.710	0.702	0.008
	[0.454]	[0.457]	
N	10,859,289	35,687,083	
Panel B: Discharges resulting in referral to a SNF			
Average daily SNF price	420.671	464.295	-43.624
	[119.808]	[114.278]	
Self-referral	0.307	-	-
	[0.461]		
Demographics			
Age	79.333	79.220	0.114
	[10.901]	[10.832]	
Female	0.641	0.635	0.005
	[0.480]	[0.481]	
Black	0.102	0.109	-0.008
	[0.303]	[0.312]	
Dual-eligibility	0.361	0.324	0.037
	[0.480]	[0.468]	
Charlson comorbidity index	1.330	1.325	0.005
	[1.512]	[1.529]	
N	2,247,952	6,411,817	

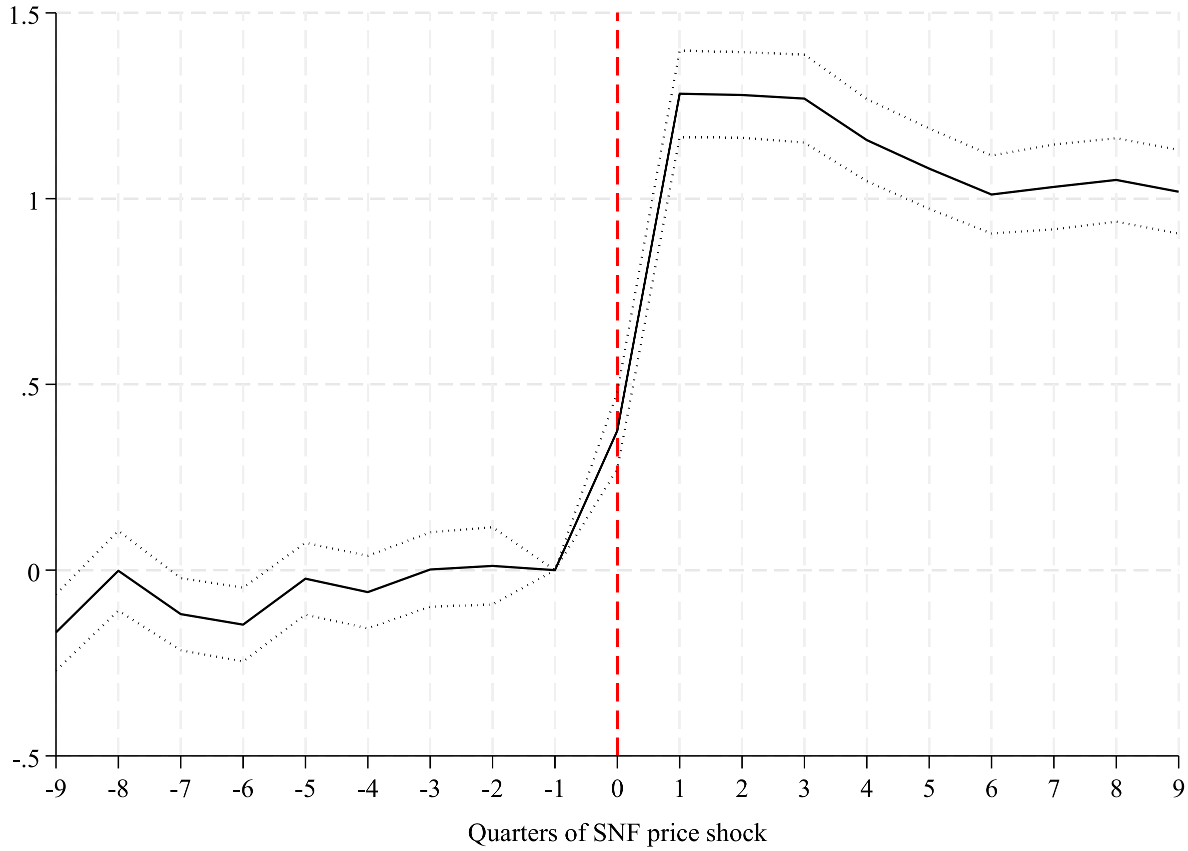
Notes: Table reports sample means for each variable. Standard deviations appear in brackets immediately beneath. Differences in means across samples are presented in the last column. The unit of observation is an inpatient Medicare discharge from hospitals within each sample group. Only observations with non-missing values for all variables are included. The sample includes 1,019 integrated hospitals (column 1) and 2,133 unintegrated hospitals (column 2). Price is defined as the average daily reimbursement for the SNF stay. Dual-eligibility refers to patients with both Medicare and Medicaid coverage.

Figure 1: Distribution of *Pred*Δ*price*



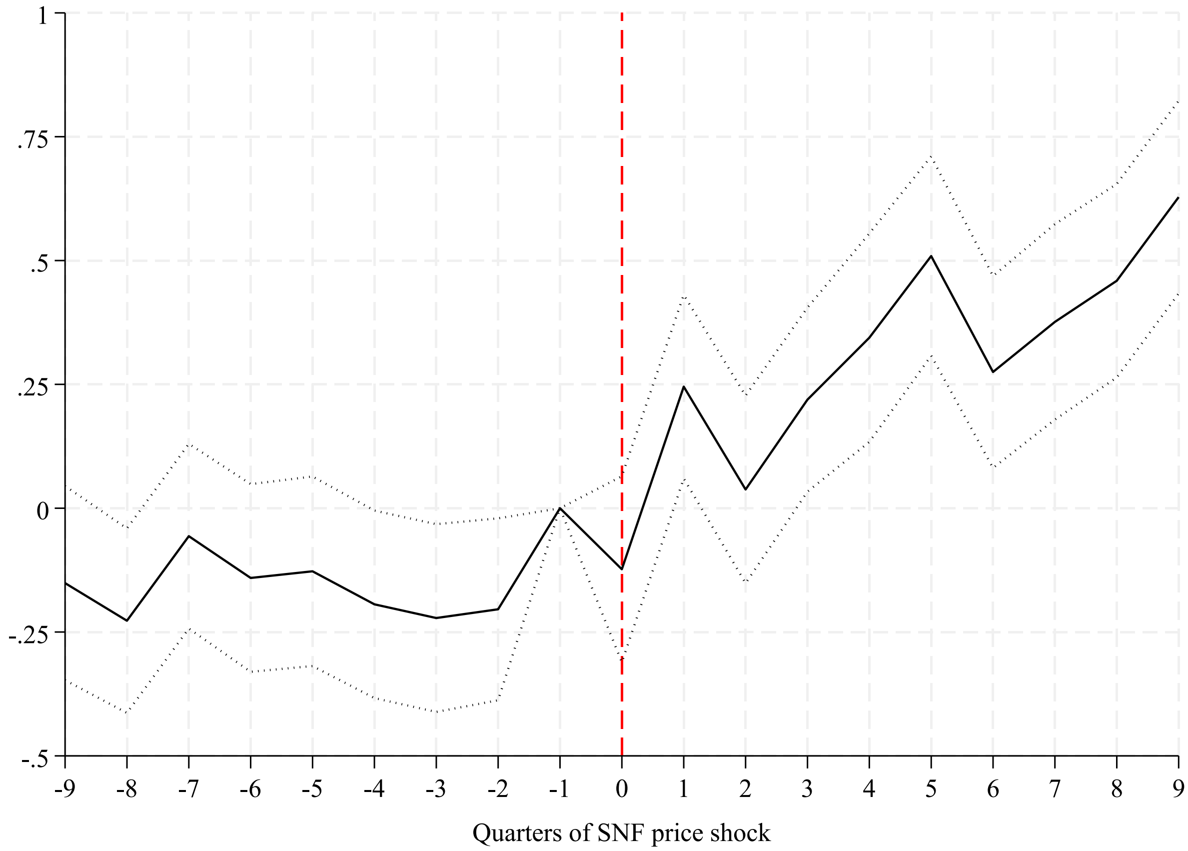
Notes: Figure reflects the distribution of *pred*Δ*price* among patients in the estimation sample. The unit of observation is an inpatient Medicare discharge (N = 50,613,359). Values of *pred*Δ*price* are winsorized at the 1st and 99th percentiles.

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 dependent variable is the log of the average daily price for the patient's SNF stay. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from integrated hospitals (N = 2,247,952). 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



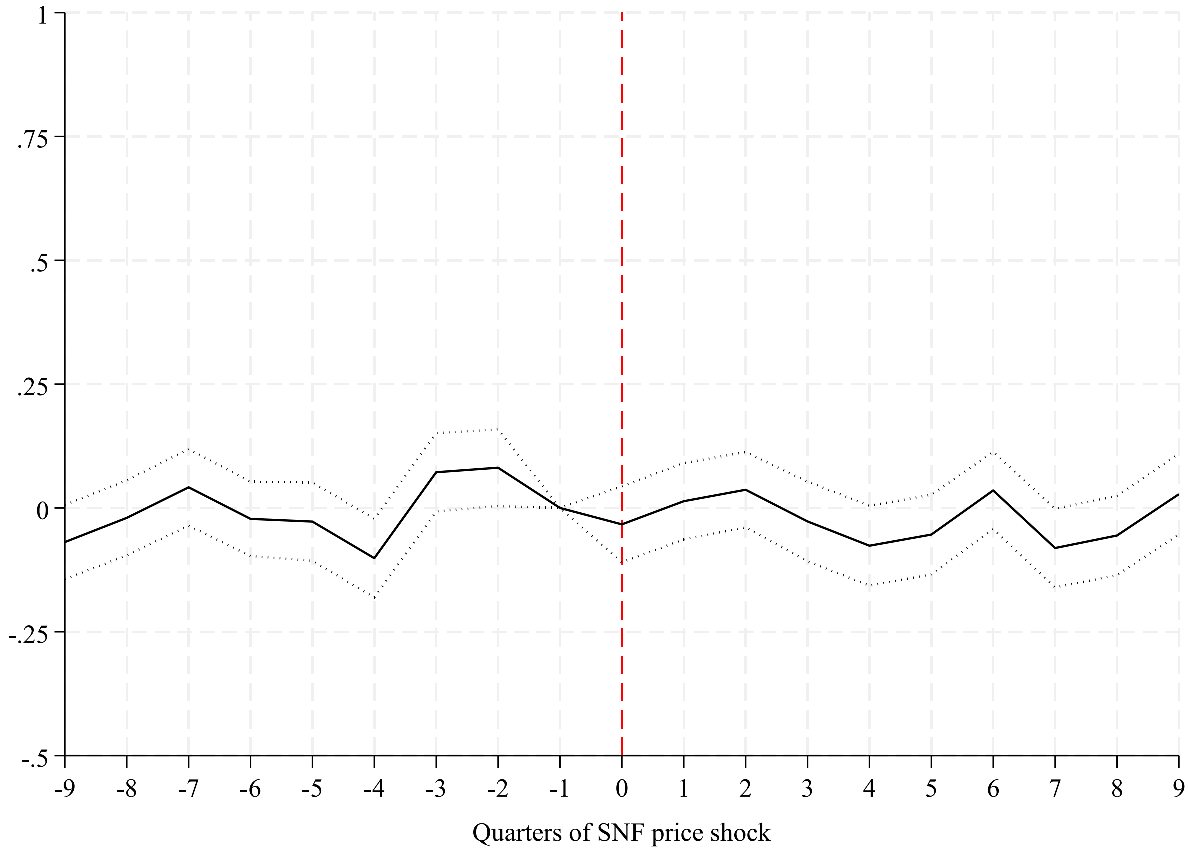
Notes: The solid line plots the coefficient estimates on the lags and leads of *pred∆price*, obtained from estimating equation (3) in the text. The dependent variable is an indicator variable for admission to a SNF owned by the discharging hospital. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from integrated hospitals (N = 2,247,952). The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects.

Table 2: Effect of *Pred∆price* on Self-Referrals

	(1)	(2)	(3)
	First-stage (Outcome: ln(price))	**Reduced form**	**2SLS**
ln(*price*)			0.199
			[0.059]
Quarter · ln(*price*)			0.050
			[0.013]
Post · *pred∆price*	1.241	0.283	
	[0.042]	[0.076]	
Post · Quarter · *pred∆price*	-0.057	0.046	
	[0.008]	[0.014]	
Quarter · *pred∆price*	0.018	0.002	-0.001
	[0.005]	[0.009]	[0.010]
Quarter = 0 · *pred∆price*	0.344	-0.011	-0.077
	[0.045]	[0.085]	[0.0080]
Combined effect of price shock in 2012Q4	0.783	0.650	0.601
	[0.072]	[0.148]	[0.134]
Dependent variable mean in pre-period	-	0.332	0.332
Self-referral elasticity	-	2.0	1.8
F Statistic	453	43	25
Observations	2,247,952	2,247,952	2,247,952

Notes: 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 in 2012Q4. Self-referral elasticity gives the percent change in self-referrals per percent change in predicted price for 2012Q4. The elasticity is effectively computed as a ratio between the reported combined effect in 2012Q4 and the dependent variable (self-referral) mean. In column (3), *Post* · *pred∆price* and *Post* · *Quarter* · *pred∆price* serve as instruments for ln*(price)* and *Quarter* · ln*(price)*. The sample includes patient discharges from integrated hospitals to SNFs from 2008Q2 to 2012Q4. Observations with missing ln*(price)* are omitted.

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 equation (5). The dependent variable is an indicator variable for admission to any SNF. The dotted lines represent a 95 percent confidence interval around the point estimates, based on standard errors clustered by *pred∆price*. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged from integrated hospitals. The model includes: (1) interactions between hospital-specific indicator variables and *pred∆price*; (2) hospital-quarter fixed effects; and (3) propensity for SNF referral control variable.

Table 3: Effect of *Pred∆price* on Referrals

	(1) SNF referral	(2) Self-referral
Post · *pred∆price*	-0.056	0.048
	[0.029]	[0.019]
Post · *Quarter* · *pred∆price*	-0.013	0.008
	[0.005]	[0.004]
Quarter · *pred∆price*	0.009	-0.008
	[0.003]	[0.002]
Quarter = 0 · *pred∆price*	-0.076	0.003
	[0.034]	[0.022]
Propensity for SNF referral	1.038	0.316
	[0.002]	[0.004]
Combined effect of price shock in 2012Q4	-0.162	0.114
	[0.059]	[0.038]
Dependent variable mean	0.210	0.068
Observations	10,843,653	10,843,653

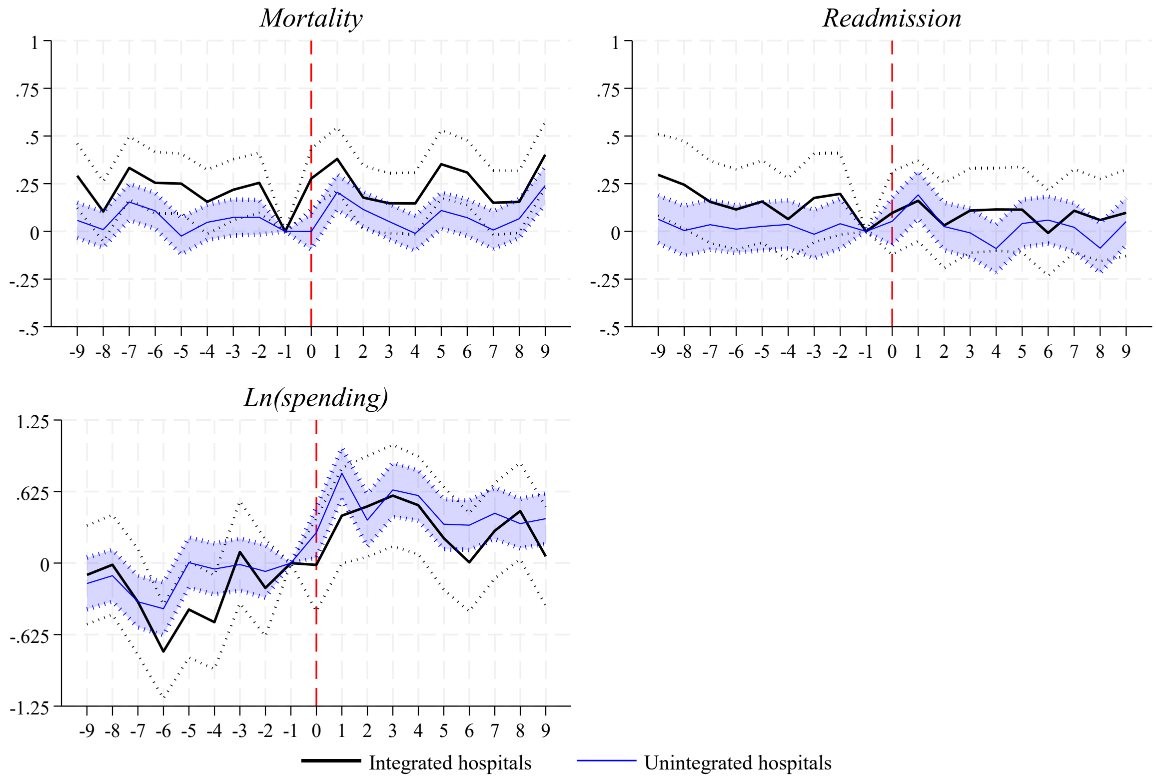
Notes: Unreported controls include: (1) interactions between hospital-specific indicator variables and *pred∆price*; and (2) hospital-quarter fixed effects. Standard errors clustered by *pred∆price* are reported in brackets. The combined effect gives the impact of the price shock on the outcome in 2012Q4. The sample includes all patient discharges (not just those resulting in SNF referrals) from integrated hospitals from 2008Q2 to 2012Q4 and excludes observations with missing data.

Table 4: Effect of *Pred∆price* on Most-Preferred SNF Referrals

		Treatment vs. Matched Comparison Sample	
Sample	**VI Hospitals Which Own Their Most Preferred SNF**	**VI Hospitals Which Own Their Most Preferred SNF**	**Non-VI Hospitals**
	(1)	**(2)**	**(3)**
Post · pred∆price	0.224	0.273	0.099
	[0.093]	[0.101]	[0.172]
Post · Quarter · pred∆price	0.079	0.104	0.017
	[0.017]	[0.018]	[0.032]
Quarter · pred∆price	0.002	-0.016	0.005
	[0.012]	[0.013]	[0.022]
Quarter = 0 · *pred∆price*	0.009	0.05	-0.005
	[0.107]	[0.115]	[0.198]
Combined effect of price shock in 2012Q4	0.852	1.107	0.237
	[0.183]	[0.200]	[0.334]
Dependent variable mean	0.403	0.399	0.398
Observations	1,668,372	1,438,455	1,457,588
Number of unique hospitals	636	566	322

Notes: 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 in 2012Q4. Column (1) is estimated using the sample of inpatient discharges to SNFs from integrated hospitals that own their most-preferred SNF. These hospitals were matched with replacement to control (unintegrated) hospitals using a matching procedure which first exact-matches on most-preferred SNF referral rate quintile bins and number of SNF discharges quintile bins and then nearest-neighbor matches on other hospital characteristics. Column (2) is estimated using these integrated hospitals matched with unintegrated hospitals, wherein a small number of hospitals included in column (1) is dropped due to lack of matches. Columns (3) is estimated using the matched unintegrated hospitals.

Figure 5: Effect of *Pred∆price* on Patient Outcomes



Quarters of SNF price shock

Notes: Each solid line within a panel plots the coefficient estimates on the lags and leads of *pred∆price* from equation (7), using different outcomes within 90 days of discharge as the dependent variable. The solid blue line for "Unintegrated hospitals" plots estimates of β^2 , and the solid black line for "Integrated hospitals" plots estimates of $\beta^2 + \beta^3$. The dotted lines and the light blue shaded area represent 95 percent confidence intervals around the point estimates, based on standard errors clustered by *pred∆price*, for the "Integrated hospitals" estimates and "Unintegrated hospitals" coefficient estimates, respectively. The dashed vertical line represents data during the transition quarter, $t = 0$. The estimation sample includes patients discharged to SNFs from integrated and unintegrated hospitals. Each estimation drops observations for which the outcome or the patient-level risk adjustment factor is not available, such that the number of observations is 8,839,160 for *mortality*, 8,877,084 for *readmission*, and 8,880,901 for ln*(spending)*. 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 based on patient demographics and hospital diagnoses.