# Regulatory Exploitation and Management Changes: Upcoding in the Hospital Industry

Leemore Dafny *Northwestern University*
David Dranove *Northwestern University*

**Abstract**

This paper investigates whether management teams that fail to exploit regulatory loopholes are vulnerable to replacement. We use the U.S. hospital industry in 1985–96 as a case study. A 1988 change in Medicare rules widened a preexisting loophole in the Medicare payment system, presenting hospitals with an opportunity to increase operating margins by 5 or more percentage points simply by "upcoding" patients to more lucrative codes. We find that having room to upcode is a statistically and economically significant predictor of whether a hospital replaces its management with a new team of for-profit managers. We also find evidence that hospitals that replace their management subsequently upcode more than a sample of similar hospitals whose management did not change.

## 1. Introduction

When the market for corporate control is efficient, managers who fail to maximize earnings will be replaced. In his seminal paper, Manne (1965, p. 119) wrote that this dynamic is "desirable from a general welfare-economics point of view." Whether such ousters (or the threat thereof) actually increase social welfare, however, clearly depends on the source of unrealized profits. In this paper, we examine changes in management resulting from the failure to exploit regulatory loopholes. As compared to managerial changes prompted by a failure to deploy productive assets efficiently, these shifts in corporate control need not increase social welfare and may even be harmful. We find empirical evidence for such managerial changes using panel data on the U.S. hospital industry between 1985 and 1996.

Leemore Dafny is also at National Bureau of Economic Research. We thank Tom Hubbard, Ilyana Kuziemko, Michael Mazzeo, Tomas Philipson, Douglas Staiger, Scott Stern, Robert Town, William White, John Gould, and an anonymous referee for helpful comments. We are grateful to Laurence Baker for sharing his data with us and to Feng Susan Lu, Michael Loquercio, and Subramaniam Ramanarayanan for expert research assistance.

[*Journal of Law and Economics*, vol. 52 (May 2009)]
 0022-2186/2009/5202-0010$10.00

The U.S. hospital industry is highly regulated at both the state and federal levels, and opportunities for exploiting regulatory loopholes abound. Our analysis is based on an unexpected change in the payment system used by Medicare to reimburse hospitals for inpatient care. This change substantially widened a preexisting loophole in the system, presenting hospitals with an opportunity to increase operating margins by several percentage points simply by reclassifying patients to more lucrative diagnostic codes, a practice known as "upcoding." Given typical operating margins of just a few percentage points during this time period, this is a substantial opportunity.

Dafny (2005) finds evidence that hospitals upcoded significantly more following the increase in the incentive to do so. The response of for-profit hospitals was significantly higher than that of nonprofit or government-owned hospitals, indicating a greater willingness or ability of for-profit managers to exploit this opportunity. This paper defines a hospital-specific, time-varying measure called "room to upcode" (RTU) and examines whether independent hospitals with higher RTU are more likely to affiliate with for-profit hospital systems following the 1988 reform. Such hospitals are good "targets" for for-profit hospital systems seeking new members, as exploiting loopholes can quickly improve a balance sheet. (As we discuss below, a hospital is said to affiliate with [or join] a system if [*a*] the hospital is sold to the system or [*b*] the hospital contracts to purchase management services from the system. Hospitals that contract for management services maintain their ownership status.)

We compare the predictors of affiliation decisions by independent hospitals during three periods: 1984–87 (the pretreatment period), 1988–92 (the treatment period), and 1992–96 (the posttreatment period, during which there was a massive federal crackdown on Medicare fraud).[1] We estimate discrete-choice models (multinomial logits) for each period, where the choice set includes the following options: join a for-profit hospital system, join a nonprofit hospital system, merge with another hospital, exit, or remain independent. Our sample for each period is restricted to independent hospitals (that is, those that do not belong to systems), as the decision to cede day-to-day management responsibilities to a hospital system is distinct from the decision to change management systems, and identifying changes in system management is very difficult because of frequent consolidations and divestments in the industry. Our focus is the impact of RTU on each option; however, we also examine whether poor operating performance precipitates affiliation changes.

We obtain three main results: (1) during the period immediately following the implementation of the new Medicare rules, independent hospitals with a higher RTU were significantly more likely to affiliate with for-profit systems; (2) hospitals that affiliated with for-profit systems during this period subsequently

[1] For each period, we take the set of independent hospitals in the first year and analyze affiliations that occur by the end of the period. We exclude affiliation changes between 1987 and 1988, as this spans the period of initial implementation. The preretreatment period is 1 year shorter than the other periods because the data are not available prior to 1985.

increased their upcoding relative to a matched sample of similar hospitals that did not; and (3) independent hospitals with higher RTU were not more likely to join for-profit systems during the pre- or posttreatment periods, nor were they significantly more likely to join nonprofit systems at any time. Our results suggest that a well-functioning market for corporate control amplifies the extent to which firms exploit regulatory loopholes.

To set the stage for our analysis, the following section describes the role of systems in the U.S. hospital industry and summarizes prior research on gaming of government regulations. Section 3 provides information on Medicare's Prospective Payment System and the regulatory change in 1988. The data are described briefly in Section 4. Section 5 presents our empirical approach together with the estimation results. Section 6 concludes.

## 2. Background

### *2.1. U.S. Hospital Systems in the 1980s and 1990s*

Over the past few decades, U.S. hospitals have been subject to increasing financial pressure exerted by public and private payers. These pressures have stimulated a major transformation of the industry, including large numbers of closures, mergers, and consolidations into hospital systems. A system consists of a group of affiliated hospitals that identify themselves as such to the American Hospital Association (AHA). System members share management and may or may not share ownership. Just as individual hospitals may be for-profit, nonprofit, or government owned, the systems to which they belong may also be for-profit, nonprofit, or government owned, and the ownership types need not be the same.

For example, consider the largest hospital system during our study period, the for-profit Hospital Corporation of America (HCA). Of 409 hospitals affiliated with HCA in 1987, 218 were directly owned (and therefore were for-profit hospitals), and 191 were managed under contracts (four for-profit, 104 nonprofit, and 83 government-owned hospitals).[2] Systems with a large number of management contracts are also known as contract management organizations, or CMOs. In the key time period that we study, the overwhelming majority of independent hospitals joining for-profit systems opted for contract management, thereby retaining control of strategic direction while ceding responsibility for day-to-day management. While most CMOs are for-profit, as the HCA example illustrates, many of their member hospitals are nonprofits. Though less common, some nonprofit systems also manage hospitals under contract, such as the Lutheran Hospital System (40 hospitals in 1987, nine managed under contract). With few exceptions, their members are nonprofit or government owned.

[2] Note that in September 1987, Hospital Corporation of America (HCA) divested 104 hospitals to an employee-owned company called HealthTrust (McCue and Clement 1992). These figures include members of both systems (American Hospital Association 1987).

Table 1
System Affiliations of U.S. General-Service Hospitals, 1984 and 1996

| Hospital Ownership | Independent | Nonprofit System | For-Profit System | Government System | Total |
|---|---|---|---|---|---|
| 1984: | | | | | |
| Nonprofit | 2,074 | 977 | 177 | 2 | 3,230 |
| For profit | 193 | 6 | 586 | 0 | 785 |
| Government | 1,254 | 103 | 166 | 28 | 1,551 |
| Total | 3,521 | 1,086 | 929 | 30 | 5,566 |
| % | 63 | 20 | 17 | 1 | 100 |
| 1996: | | | | | |
| Nonprofit | 1,546 | 1,129 | 201 | 2 | 2,878 |
| For profit | 128 | 7 | 550 | 0 | 685 |
| Government | 932 | 131 | 156 | 29 | 1,248 |
| Total | 2,606 | 1,267 | 907 | 31 | 4,811 |
| % | 54 | 26 | 19 | 1 | 100 |

**Source.** American Hospital Association (1984–96a, 1984–96b).

Whether through ownership or long-term contracts, systems provide comprehensive management of the hospital operations and can bring expertise in the areas of billing, medical records, labor management, marketing, and information technology, including processes and software used for diagnostic coding (Alexander and Morrisey 1989).[3] Systems may also provide increased access to capital and negotiate joint contracts with suppliers and insurers. Because system members enjoy these benefits regardless of ownership versus contract status, we hypothesize that both owned and contracting hospitals will enjoy similar benefits. Unfortunately, during our study period only a handful of independent hospitals ceded ownership to for-profit systems, precluding an exploration of potential differences in the factors affecting the choice of ownership mode.[4]

Table 1 gives the ownership status of hospitals and the systems to which they belong in 1984 and 1996; these figures derive from the American Hospital Association's *Annual Survey of Hospitals* and *Guide to Hospitals*.[5] All ownership types are represented in for-profit and nonprofit systems. Government systems are extremely small and consist of government-owned hospitals and a handful of nonprofit hospitals; for this reason, we do not consider affiliation with a government-owned system as an outcome in our discrete choice models. Between 1984 and 1996, system affiliation increased from 37 to 46 percent. The increase

[3] Diagnostic coding by hospitals falls under the rubric of compliance. Quorum, the largest contracting firm (and a spinoff of HCA), identifies compliance as a key management support task they provide to contracting hospitals (QHR Management Services, Compliance Client Services Support [http://www.qhr.com/qhr2.nsf/View/ComplianceServicesSupport]). The Quorum Health Resources Learning Institute also offers contracting members a series of courses on coding.

[4] We confirm that the results are similar when the option of joining a for-profit system and converting to for-profit ownership is considered as a separate choice in the multinomial logit framework.

[5] See the Appendix for a description of how system membership and ownership is determined using data from the American Hospital Association.

in affiliation was particularly pronounced among nonprofit and government-owned hospitals.

The health economics literature on hospital systems informs our analysis and helps to frame the findings. Cuellar and Gertler (2005) show that system membership is more likely among hospitals that are for profit, located in urban areas, or have high managed-care loads. Alexander and Morrisey (1989) and Alexander and Lewis (1984) find that smaller hospitals and hospitals with weak financial performance are most likely to join CMOs. According to industry publications, some CMOs specifically targeted financially distressed hospitals during this time period (see, for example, *Modern Healthcare* 1990). Taken together, these studies suggest that hospital characteristics, including financial performance and ownership status, are predictors of system affiliation. We include all of these variables in our analysis of system affiliation decisions, although our primary focus is Room to Upcode, a hospital-specific measure of forgone opportunities to game government regulations. As for differences across systems by ownership status, Mobley (1997) documents that nonprofit systems tend to consist of multiple hospitals in a local market area, while for-profits have broader geographic spread. Dafny (2005) and Silverman and Skinner (2004) find that for-profit hospitals upcode more than hospitals of other ownership forms and that most for-profit hospitals belong to for-profit systems. These patterns suggest that the upcoding strategies of nonprofit and for-profit systems may differ, a prediction we consider in the empirical work that follows.

### *2.2. Gaming Governmental Regulations*

To our knowledge, there are no prior studies that examine regulatory exploitation as a motive for managerial changes. However, a long literature documents firms' responses to regulatory incentives, dating back to Averch and Johnson's (1962) paper on investment by public utilities subject to rate-of-return regulation. More recent papers include Duggan and Scott Morton (2006) and Kyle (2007) on pharmaceutical companies' responses to price regulation, Desai and Hines (2002) on American corporations' efforts to avoid U.S. taxes on foreign income, and Goolsbee (2000), Rose and Wolfram (2002), and Hall and Liebman (2000), among others, on the responsiveness of executive compensation to tax incentives. The possibility that managerial selection could be influenced by the ability or willingness to take advantage of regulatory loopholes follows naturally from this research.

## 3. Room to Upcode: A Measure of Forgone Opportunities to Exploit Medicare Reimbursement Policies

Our empirical analysis focuses on a policy change that generated plausibly exogenous variation in the potential profits from upcoding within individual hospitals. This section describes Medicare's reimbursement system, the policy change that increased the payoff to upcoding, and the formula we use to measure

RTU for each hospital and year. In the data section, we describe other variables in our analysis of system affiliation, including a measure of hospital operating efficiency.

### *3.1. Medicare Payment Rules and Opportunities for Exploitation*

The federal Medicare program accounts for nearly one-third of hospital revenues nationwide and is the largest payer for most hospitals (Winter and Pettengill 2003). Prior to 1984, Medicare reimbursed inpatient stays on a fee-for-service (that is, cost-plus) basis. Under the Prospective Payment System (PPS) introduced in 1984, Medicare pays hospitals a fixed fee per admission, where the fee depends on the patient's primary medical condition or diagnosis-related group (DRG). The payment formula can be approximated as

$$P_{\mathrm{hd}} = P_{\mathrm{h}} \times (1 + \mathrm{IME}_{\mathrm{h}}) \times (1 + \mathrm{DSH}_{\mathrm{h}}) \times \mathrm{DRG\ weight}_{\mathrm{d}}, \tag{1}$$

where h indexes hospitals and d indexes DRGs, $P_{\mathrm{h}}$ is a hospital-specific base payment amount (inflated annually by a congressionally approved update factor), $\mathrm{IME}_h$ represents a (positive) adjustment factor for indirect medical education (that is, teaching), and $\mathrm{DSH}_{\mathrm{h}}$ adjusts payment levels to compensate hospitals with a disproportionate share of indigent patients.[6]

The DRG weights reflect the relative resource intensity of admissions to each DRG and are recalculated each year by taking the ratio of average nationwide costs in each DRG to average nationwide costs for all hospitalizations. In 1990 (midway through our study period), the maximum weight of 13.4638 was associated with admissions for respiratory system diagnosis with tracheostomy, while admissions for false labor earned the minimum weight of .1186. The case-mix index for a hospital is the average DRG weight of its admissions.

Hospitals are responsible for assigning patients to the appropriate DRGs. The consequences of inappropriate assignment are potentially quite serious. Patient care may be compromised if hospitals manipulate medical records or alter treatment for the purpose of maximizing reimbursement. The fairness of Medicare payment rates to all hospitals depends on the accuracy with which each hospital assigns DRGs. If, for example, some hospitals assign relatively healthy patients to a more remunerative DRG reserved for severe cases, the nationwide payment rate for that DRG will decline.

Despite the need for accuracy, this system provides a strong incentive to upcode patients into the most remunerative DRGs. Upcoding encompasses a broad set of actions, ranging from careful documentation of all comorbidities to ensure appropriate reimbursement to liberal interpretation of rules to outright manipulation of the patient record. When upcoding involves intentionally misstating the diagnosis, it rises to the level of fraud and is covered under the amendments

[6] This simplified formula appears in Cutler (1995).

to the federal False Claims Act (31 U.S.C. 3729 [1986]). The medical profession also considers this to be a breach of ethics.[7]

Successful upcoding that enhances revenues without rising to the level of fraud requires careful attention to medical records, sophisticated software, and trained coding personnel. Hospital systems may therefore enjoy substantial expertise and economies of scale arising from centralized coding efforts. The ownership status of a system may also influence upcoding behavior among system members. Prior studies find that for-profit hospitals upcode more, and most for-profit hospitals belong to for-profit systems. The difference in upcoding rates may be due to differences in owners' or managers' willingness to upcode and/or to differences in the incentives provided to managers. For example, one for-profit hospital chain based managerial bonuses on the coded incidence of complications (Lagnado 1997, pp. A1, A6). Silverman and Skinner (2004) also suggest that for-profit hospitals may have a greater willingness to bear the risk of regulatory enforcement. Nonprofit owners and managers may avoid the "gray areas" of upcoding in order to preserve their "trust capital" in the community (Glaeser et al. 2000). Many studies find that when it comes to balancing profits against more altruistic objectives such as providing community benefits, for-profit hospitals lean more heavily toward profits (see, for example, Roomkin and Weisbrod 1999; Brickley and Van Horn 2002; Horwitz 2005).[8] These findings notwithstanding, Dranove's (1988) study of pricing by nonprofit hospitals finds that nonprofits are more likely to focus on profit maximization when in financial peril. This result suggests that struggling nonprofits may be more willing to seek help from for-profit systems, even if this decision compromises their ethics and/or altruistic pursuits.

### *3.2. The 1988 Change in Coding*

Although upcoding was known to be a problem with PPS since its inception, a change to the DRG coding system in 1988 offered hospitals substantial and relatively easy opportunities to upcode. The change pertained to DRG codes belonging to a DRG pair. A DRG pair consists of two codes for the same diagnosis. Of 473 codes in 1987, 190 belonged to DRG pairs. Prior to 1988, the top code within a pair was utilized for all patients over age 69 and younger patients with complications (CC); the bottom code was for younger patients with the same diagnosis but without complications. Analyses performed in 1987 revealed that, on average, charges for patients with CC were much higher than charges for

[7] For example, the American Academy of Otolaryngology states that it is "unethical for a physician to charge an illegal fee" and includes upcoding as an example. See American Academy of Otolaryngology—Head and Neck Surgery, Ethics (http://www.entlink.net/academy/policies/ethics.cfm).

[8] This raises the question of why a hospital that did not upcode prior to joining a system would agree to join a system that intended to upcode. First, the hospital may have lacked the skills and/or software needed to upcode while independent. Second, the hospital may not be aware that the new system intends to boost revenues via upcoding. Third, owners who are aware of a system's intention to upcode may believe that system management is a last-resort solution needed to stay open and that their responsibility to eschew upcoding ends when they outsource management.

patients without CC, but older patients were not significantly more expensive to treat than younger patients (who were primarily aged 65–69). The Centers for Medicare and Medicaid Services (CMS) concluded that "in all but a few cases, grouping patients who are over 69 with the CC patients is inappropriate" (52 Fed. Reg. 18,877 [1987]), so the agency removed the age qualifiers and recalculated the DRG weights using the new categories.

Table 2 provides examples of the three most common DRG pairs and their DRG weights before and after the policy change. The recalibration following the policy change produced a weighted average increase of 11.3 percent in the payments for top codes and a decrease of 6.2 percent in the payments for bottom codes. This resulted in a substantial increase in the value of coding complications, as compared to the preceding years (1984–87). Given a typical $P_h$ of $3,165 in 1988, the increase in revenues associated with coding complications was approximately $550 per admission (or $800 in year 2000 dollars).[9]

We define RTU as the increase in a hospital's average DRG weight (the case-mix index) that would result from a shift of all patients in bottom codes of DRG pairs to the associated top codes. We calculate this measure for each hospital and year using a 20 percent sample of Medicare discharges from the CMS's Medicare Provider Analysis and Review (MEDPAR) database, described below. Given that hospitals in 1987 had an average case-mix index of 1.14, RTU is approximately equal to the percentage increase in Medicare revenues that a hospital could obtain by coding all patients with complications. (As equation [1] indicates, RTU is exactly equal to the percentage increase in revenues if the initial case-mix index is 1.) We multiply RTU by 100 to facilitate the presentation of our results.

Figure 1 presents annual box plots of RTU for all general community hospitals in the nonterritorial United States except for-profit system members, whose distributions are presented separately in Figure 2. The figures pertain to general, nonfederal, nonstate hospitals in the nonterritorial United States with 50 or more discharge records in the MEDPAR database. The bars correspond to the 5th, 25th, 50th, 75th, and 95th percentiles in each year. The large average increase in RTU in 1988 reflects the policy change; the steady decline thereafter reflects the subsequent increase in upcoding. Although the distribution of RTU is very similar for the two samples in the years prior to the policy change, the jump in RTU is smaller, suggesting that system members increased upcoding within the first year of the policy change, and the decline between 1988 and 1989 is particularly steep. (Specifically, median RTU among hospitals that are not for-profit system members increased from 1.4 in 1987 to 6.6 in 1988 and decreased to 5.8 by 1989, whereas median RTU among for-profit system members increased from 1.3 in 1987 to 6.0

[9] See National Adjusted Standardized Amounts, Labor/Nonlabor, table 1A in Medicare Program; Changes to the Inpatient Hospital Prospective Payment System and Fiscal Year 1988 Rates (52 Fed. Reg. 33,034 [1987]). In 1988, $3,165 was the standardized amount for urban hospitals; 1988 dollars were converted to 2000 dollars using the Consumer Price Index for All Urban Consumers (CPI-U).

**Table 2**

**Examples of Policy Change**

| DRG Code | Description | | Weight | | % Change in Weight |
|---|---|---|---|---|---|
| | 1987 | 1988 | 1987 | 1988 | |
| 96 | Bronchitis and asthma age >69 and/or complications | Bronchitis and asthma age >17 with complications | .8446 | .9804 | 16 |
| 97 | Bronchitis and asthma age 18–69 without complications | Bronchitis and asthma age >17 without complications | .7091 | .7151 | 1 |
| 138 | Cardiac arrhythmia and conduction disorders age >69 and/or complications | Cardiac arrhythmia and conduction disorders with complications | .8136 | .8535 | 5 |
| 139 | Cardiac arrhythmia and conduction disorders age <70 without complications | Cardiac arrhythmia and conduction disorders without complications | .6514 | .5912 | −9 |
| 296 | Nutritional and miscellaneous metabolic disorders age >69 and/or complications | Nutritional and miscellaneous metabolic disorders age >17 with complications | .8271 | .9259 | 12 |
| 297 | Nutritional and miscellaneous metabolic disorders ages 18–69 without complications | Nutritional and miscellaneous metabolic disorders age >17 without complications | .6984 | .5791 | −17 |

**Source.** Dafny (2005).
**Note.** Of the 95 diagnosis-related group (DRG) pairs, these three occur most frequently in the 1987 20 percent Medicare Provider Analysis and Review sample. The DRG weights are from 51 Fed. Reg. 31,454 (1987) and 52 Fed. Reg. 33,034 (1988).

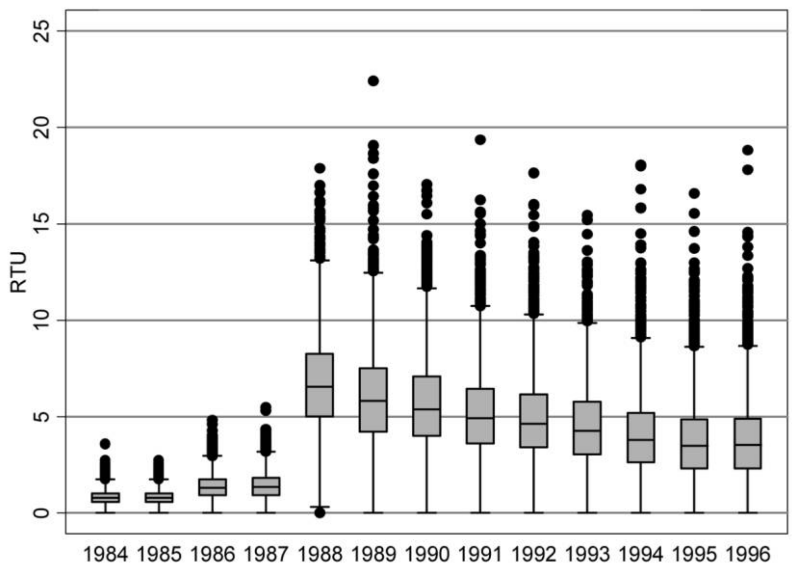


**Figure 1.** Annual distribution of room to upcode, 1984–96: all community hospitals except for-profit system members.

in 1988 and decreased to 4.8 in 1989.)[10] Box plots for nonprofit system members are not presented separately, as they are very similar to Figure 2.

The variation in RTU across hospitals in a given year is driven by differences in upcoding practices, the true complication rate, and the share of patients in DRG pairs. A higher true CC rate will diminish RTU if a hospital is already reporting all complications. A hospital with a low incidence of cases in DRG pairs will also have a low RTU. The share of patients in DRG pairs also depends on upcoding proclivity, as hospitals may assign patients to paired DRGs instead of unpaired DRGs if it is financially advantageous to do so. (Dafny [2005], however, finds no evidence of this practice in the years immediately following the policy change.) The term RTU can be viewed as a proxy for room to exploit reimbursement regulations more generally, as hospitals failing to code complications are likely to be forgoing other similar opportunities.[11]

[10] A two-sample *t*-test fails to reject equality of the 1987 means for the two samples ($p = .35$) but easily rejects equality of the 1988 means ($p < .01$).

[11] The term RTU does not fully capture all upcoding possibilities available to a hospital. First, many private insurers use the same DRG system, or a different system that also rewards upcoding. Second, there are other diagnoses that present opportunities for upcoding. Third, there are opportunities to upcode outpatients. In addition, the Medicare system is also susceptible to activities similar to upcoding, such as excessive charging for certain treatments in order to qualify for outlier payments. The term RTU might therefore serve as an indicator of whether a hospital is taking full advantage of Medicare rules. Note that RTU is measured with error because it is calculated from a random sample of discharges and because upcoding is more difficult to detect (and therefore to penalize) in

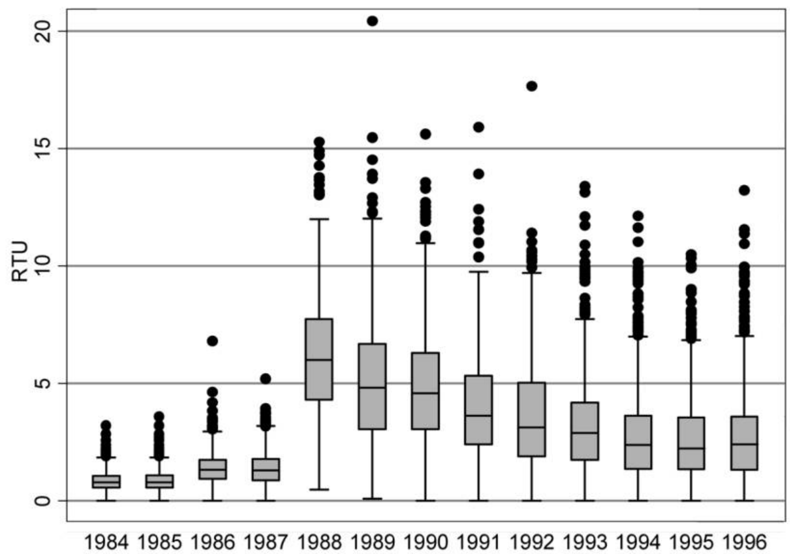


**Figure 2.** Annual distribution of room to upcode, 1984–96: for-profit systems with three or more members.

For all of these reasons, RTU cannot be assumed exogenous and may be associated with other factors that affect the propensity of independent hospitals to join systems. Our identification strategy for the RTU effect relies on defining a specific treatment period following the 1988 policy change and comparing system affiliation by independent, high-RTU hospitals during this period with affiliation patterns in the preceding (and following) years.

### *3.3. Defining the Treatment Period*

Although the 1988 reform substantially heightened the incentive to upcode, the window to do so effectively ended a few years later. By the early 1990s, researchers and policymakers were raising red flags about the practice. Several prominent academic papers on upcoding appeared in the early 1990s, including a 1993 *New England Journal of Medicine* article exposing systematic upcoding to increase reimbursement by hospitals in New England (Assaf et al. 1993). The Federal Bureau of Investigation ramped up its health care antifraud efforts in 1992; within 3 years, it had nearly tripled the number of agents working exclusively on health probes (Andeson 1995, p. A6). In 1994, Senator William Cohen proposed tougher penalties for health care fraud, citing national research indi-

---

some diagnoses than in others. Assuming that this error is uncorrelated with omitted determinants of new system affiliations, our estimates suffer from attenuation bias and should therefore be viewed as conservative.

cating annual costs of as much as $100 billion (Lipman 1995, p. A13). A *Boston Globe* exposé that year suggested that "of all the areas under investigation (by the Department of Health and Human Services), it is coding fraud that might be the most prevalent and costly" (Golden and Kurkjian 1994, p. 1). In January 1995, Cohen took over as chair of the Senate Special Committee on Aging, where he promised to continue investigations of health care fraud.[12] In 1996, many of his earlier proposals were incorporated into the Health Insurance Portability and Accountability Act (HIPAA), which requires national standards for health care services and outlines various specific new penalties.[13]

By the mid-1990s, payers were also responding to the challenge of detecting upcoding. Since the inception of PPS, coding for Medicare patients has been audited by peer review organizations, or PROs, who are responsible for "ensur[ing] that Medicare hospital services are appropriate, necessary, and provided in the most cost-effective manner" (U.S. Department of Health and Human Services 2001, p. 4). Beginning in 1995, the Health Care Financing Administration contracted with two clinical data abstraction centers to validate the accuracy of DRG coding. Together with the Office of the Inspector General, these centers identified DRGs and hospitals prone to upcoding and instructed PROs to take actions to eliminate "erroneous billing."[14] As of 1996, at least six vendors had developed software to help private payers detect upcoding (U.S. Department of Health and Human Services 1998). Given the resources allocated to halting upcoding and the threats of criminal prosecution, we anticipate that the upcoding motive for system affiliation lessened substantially by the early 1990s. Our main analysis therefore focuses on the effect of RTU on system affiliations between 1988 and 1992, immediately after opportunities to upcode Medicare patients increased. We contrast these results with affiliations during 1984–87 (the pretreatment years for which data are available) and 1992–96. (Affiliations between 1987 and 1988 are not examined for reasons explained below.) As a robustness check, we also confirm that the results are similar when the treatment period extends through 1993, leaving 1993–1996 as the posttreatment period.

[12] After a 3-year investigation by the Department of Justice, National Medical Enterprises agreed in 1994 to pay a cash settlement in excess of $350 million, the largest health care fraud settlement in U.S. history (at the time) (see Thomas 1994, p. A12). This record has since been broken by settlements with two large for-profit hospital chains, Tenet Healthcare Corporation ($725 million) and Columbia/HCA ($1.7 billion) (see Rundle 2006, p. B1; O'Harrow 2002, p. E01). Contract management organizations (CMOs) have also faced charges of fraud. In 2001, the largest CMO (Quorum Health Group Inc., which manages over 200 hospitals) paid a cash settlement of $103 million for defrauding the Medicare program by "systematically misrepresenting reimbursable expenditures" across hospitals it managed (Eichenwald 2000, p. A21).

[13] Details are available at Department of Health and Human Services, Centers for Medicare and Medicaid Services, HIPAA—General Information (http://www.cms.hhs.gov/HIPAAGenInfo).

[14] These centers reviewed tens of thousands of inpatient records of Medicare patients with selected diagnoses that are prone to upcoding, such as septicemia and metabolic disorders. See, for example, U.S. Department of Health and Human Services (1999).

## 4. Data

We use the *Annual Survey of Hospitals* conducted by the AHA in 1984–96 to identify hospitals and system affiliations and to obtain descriptive characteristics such as number of beds and services provided. The RTU for each hospital-year is calculated using the annual DRG weights published in the *Federal Register*[15] and the 20 percent Medicare Provider Analysis and Review (MEDPAR) data set for fiscal years 1985–96. This data set is a random 20 percent sample of discharge records (including DRG codes and hospital identifiers) for Medicare hospitalizations. Hospital financial data for fiscal years 1985–96 are obtained from the Healthcare Cost Report Information System (HCRIS) data sets, also known as the Medicare Cost Reports. Finally, the Medicare case-mix index, which we use as a control variable, is extracted from the Medicare PPS Impact Files, a hospital-level database of PPS-related variables.

Our sample is restricted to nonfederal, nonstate, general-service hospitals located in the nonterritorial United States. For each time period we examine (1984–87, 1988–92, 1992–96), we include only those hospitals that were independent (that is, unaffiliated with a system) as of the first year (for example, 1984). The Appendix describes our methods for cleaning the AHA's system identifier and for determining the ownership status of each system. We exclude hospitals in any year in which they have fewer than 50 observations in the MEDPAR sample, which is used to calculate RTU; RTU is very noisily measured when the number of admissions is low.[16] We also drop hospitals with religious affiliations, as none joined for-profit systems during the study period. Last, we exclude hospitals with 30 or fewer beds; only one out of 118 such hospitals joined a for-profit system during the treatment period. Table A1 lists the number of hospitals excluded by each sample restriction for each of the three time periods.

Table 3 presents the affiliation decisions made by independent hospitals during each study period. Only affiliations with systems of two or more hospitals (so three or more total) are counted. This restriction is irrelevant for for-profit systems and is imposed to improve comparability of the for-profit and nonprofit affiliation decisions; it also reduces the impact of potential coding errors in the data. Values are presented separately by initial ownership status of the hospital. When system affiliation coincides with a change in ownership form, this too is reported. For example, of the 902 independent government hospitals in 1984, 56 had joined a for-profit system by 1987, and six of these converted to for-

[15] See 48 Fed. Reg. 39,838 (1984), 49 Fed. Reg. 324 (1985), 50 Fed. Reg. 35,646 (1986), 51 Fed. Reg. 31,454 (1987), 52 Fed. Reg. 33,034 (1988), 53 Fed. Reg. 38,476 (1989), 54 Fed. Reg. 19,636 (1990), 55 Fed. Reg. 35,990 (1991), 56 Fed. Reg. 43,196 (1992), 57 Fed. Reg. 39,746 (1993), 58 Fed. Reg. 30,221 (1994), and 59 Fed. Reg. 45,330 (1995).

[16] Approximately 40 percent of Medicare admissions are assigned to DRG pairs, so hospitals with fewer than 50 admissions have fewer than 20 discharge records, on average, that can generate a positive RTU (if they are assigned to bottom codes).

Table 3
New Affiliations by Independent Hospitals, by Ownership Status

| Study Period | Stay Independent | Join Nonprofit System (and Convert) | Join For-Profit System (and Convert) | Join Government System (and Convert) | Exit | Merge | Total |
|---|---|---|---|---|---|---|---|
| 1984–87: | | | | | | | |
| Nonprofit | 1,471 | 86 (N.A.) | 64 (12) | 0 (0) | 1 | 0 | 1,622 |
| For profit | 72 | 3 (0) | 17 (N.A.) | 0 (0) | 0 | 0 | 92 |
| Government | 794 | 49 (9) | 56 (6) | 3 (N.A.) | 0 | 0 | 902 |
| Total | 2,337 | 136 (9) | 139 (18) | 3 (0) | 1 | 0 | 2,616 |
| 1988–92: | | | | | | | |
| Nonprofit | 1,322 | 43 (N.A.) | 43 (3) | 0 (0) | 36 | 38 | 1,482 |
| For profit | 70 | 0 (0) | 4 (N.A.) | 0 (0) | 10 | 4 | 88 |
| Government | 673 | 24 (6) | 28 (1) | 1 (N.A.) | 15 | 9 | 750 |
| Total | 2065 | 67 (6) | 75 (4) | 1 (0) | 61 | 51 | 2,320 |
| 1993–96: | | | | | | | |
| Nonprofit | 1,120 | 152 (N.A.) | 67 (24) | 0 (0) | 22 | 65 | 1,426 |
| For profit | 62 | 7 (4) | 18 (N.A.) | 0 (0) | 10 | 4 | 101 |
| Government | 573 | 48 (12) | 49 (10) | 1 (N.A.) | 7 | 9 | 687 |
| Total | 1,755 | 207 (16) | 134 (34) | 1 (0) | 39 | 78 | 2,214 |

**Note.** Only new affiliations with systems of at least two other hospitals are reported. Ownership status of systems in this sample was verified for all system sizes using American Hospital Association (1984–96b) N.A. = not applicable.

profit status.[17] Owing to the small number of system affiliation plus conversions, we do not consider this to be an outcome separate from affiliation itself. As noted above, we also do not consider affiliation with government systems as an outcome because of the infrequency with which it occurs. When estimating the discrete-choice model, we assign the handful of hospitals that do join government systems to the baseline choice of "stay independent."

Of 2,320 independent hospitals in 1988 (the start of the treatment period), 67 joined nonprofit systems, 75 joined for-profit systems, 61 exited, and 51 merged by 1992. Affiliation activity was significantly higher during the pretreatment and posttreatment periods than during the treatment period. These aggregate differences likely reflect responses to the implementation of PPS (and its burdensome regulations) during the early period and to growing managed-care penetration in the later period. However, our objective is not to explain these aggregate patterns but rather to understand why particular hospitals affiliate with systems during a given period. In the following section, we describe the way in which we use data from each period and the assumptions underlying our approach.

Table 4 lists the sources for all independent variables and presents summary

[17] Note that system affiliations are counted if they occur at any point during the time period in question; they need not be active in the final year of the period.

**Table 4**

**Descriptive Statistics, by Time Period**

| Variable | Source | 1984–87 | 1988–92 | 1992–96 |
|---|---|---|---|---|
| RTU | MEDPAR | .814 | 6.64 | 4.98 |
| | | (.353) | (2.50) | (2.17) |
| Residual profit | HCRIS | .527 | .798 | .572 |
| | | (7.35) | (7.97) | (7.34) |
| Hospital controls | American Hospital Association (1984–96a) | | | |
| For-profit (%) | | 3.5 | 3.8 | 4.6 |
| Government (%) | | 34.5 | 32.3 | 31.0 |
| Nonprofit (%) | | 62.0 | 63.9 | 64.4 |
| Teaching (%) | | 6.8 | 6.5 | 5.7 |
| Number of beds (%) | | | | |
| 30–49 | | 13.8 | 15.2 | 14.8 |
| 50–99 | | 26.8 | 24.3 | 24.3 |
| 100–199 | | 25.6 | 26.2 | 26.6 |
| 200–299 | | 14.4 | 16.3 | 16.2 |
| 300–399 | | 8.4 | 8.5 | 8.4 |
| 400–499 | | 5.1 | 4.4 | 4.0 |
| 500+ | | 6.0 | 5.0 | 5.6 |
| Medicare share of discharges | American Hospital Association (1984–96a) | .372 | .383 | .419 |
| | | (.108) | (.105) | (.115) |
| Medicaid share of discharges | American Hospital Association (1984–96a) | .102 | .119 | .164 |
| | | (.071) | (.084) | (.106) |
| Medicare case mix index | Medicare Impact Files | 1.096 | 1.175 | 1.229 |
| | | (.119) | (.153) | (.200) |
| Count of high-technology services | American Hospital Association (1984–96a) | 1.352 | 1.621 | 1.927 |
| | | (1.698) | (1.705) | (1.740) |
| Market controls: | | | | |
| MSA population (%) | American Hospital Association (1984–96a) | | | |
| Not in MSA | | 49.8 | 47.5 | 44.6 |
| <100,000 | | 1.1 | 1.3 | 1.0 |
| 100,000–249,999 | | 8.6 | 9.2 | 8.1 |
| 250,000–499,999 | | 8.1 | 8.3 | 8.4 |
| 500,000–999,999 | | 9.4 | 10.3 | 7.5 |
| 1,000,000–2,500,000 | | 13.0 | 12.5 | 13.3 |
| >2,500,000 | | 10.0 | 10.9 | 17.1 |
| County HMO penetration | Baker (1997)[a] | .099 | .099 | .115 |
| | | (.111) | (.110) | (.116) |
| Zip code per capita income | U.S. Census (2000) | 19,353 | 19,557 | 19,569 |
| | | (7,580) | (7,785) | (7,565) |
| Zip code % black | U.S. Census (2000) | .125 | .128 | .126 |
| | | (.190) | (.191) | (.189) |
| Zip code % urban | U.S. Census (2000) | .712 | .724 | .732 |
| | | (.303) | (.295) | (.286) |
| *N* | | 2,616 | 2,320 | 2,214 |

**Note.** Variables are available annually unless otherwise specified and are measured as of the first year in each time period, with the following exceptions: RTU, residual profit, and case mix index for the first period are reported as of 1985. Baker's HMO penetration estimates are derived using data from the Group Health Association of America (1990–94) and Interstudy (1995–96). We use Baker's 1990 estimates for all regressions utilizing data prior to (and including) 1990. For hospitals in zip codes that do not appear in the 2000 census files, we use census data for the corresponding zip code from a later year; if unavailable, we assign the state-level mean values. Per capita income squared is included in all regressions with control variables. RTU and residual profit are multiplied by 100, so that both can be interpreted (approximately) as percentage points. MEDPAR = Medicare Provider Analysis and Review; HCRIS = Healthcare Cost Report Information System; MSA = metropolitan statistical area; HMO = health maintenance organization.

[a] Annual for 1990–96.

statistics for each study period. Variables are measured as of the initial year in each period, except when unavailable (as noted). Given that the initial values for each period are used as predictors, it is now apparent why affiliations in 1987–88 cannot be included. On the one hand, these affiliations may reflect the 1988 reform, so they cannot be included in the pretreatment period. On the other hand, including them in the treatment period would entail using 1987 RTU as the predictor of affiliations during that period, and the policy-induced RTU jump occurred in 1988.[18]

The independent variables included in all models are as follows:

*Room to Upcode (RTU).* As described above, RTU is the increase in a hospital's average DRG weight that would result if the hospital assigned all patients currently in the bottom codes of DRG pairs to the associated top codes. It is approximately equal to the percentage increase in Medicare revenues available via upcoding in DRG pairs and is multiplied by 100 to facilitate the presentation of the results.

*Residual Profits.* To obtain a measure of how well a hospital is performing relative to expectations, we calculate the residual from a regression of operating margins on a large set of observable hospital and market covariates commonly used in the health economics literature (listed below). These regressions are estimated separately by year, using the entire sample of nonfederal, nonstate community hospitals in the nonterritorial United States (that is, including hospitals that are not independent).[19] Ceteris paribus, a well-run hospital should be less likely to seek or be targeted by a system. We also multiply the residual margin by 100 to facilitate the presentation of the results.

*Hospital Controls.* These are ownership type (for-profit, nonprofit, government), membership in the Council of Teaching Hospitals, seven dummies for number of beds, Medicare share of discharges, Medicaid share of discharges, and the level of technological sophistication as measured by a count of high-technology services (cardiac catheterization lab, certified trauma center, computed tomography scanner, megavoltage radiation therapy, and open-heart surgery).

*Market Controls.* These include seven dummies for population of the metropolitan statistical area, county-level health maintenance organization penetration (among the nonelderly), and zip code demographics (per capita income and its square, percentage of the population that is black, and percentage of the population that is urban).

All specifications include dummies for nine geographic regions identified by

[18] Note that the 1-year lag is intentional: systems identifying targets for 1988 would presumably need historical data to predict the increase in revenue that could be obtained from upcoding, and these data are available only with a lag.

[19] Profits are censored at the 5th and 95th percentiles to reduce the influence of outliers. The specification also includes state fixed effects. The adjusted $R^2$ value for each year is ~.20. Results are available by request.

the AHA.[20] These dummies primarily capture differences in the prevalence of for-profit chains across the country. These chains are most active in the South and the West.

## 5. Empirical Analysis

### 5.1. *Effect of Room to Upcode on Affiliation Decisions*

To examine the predictors of hospital affiliations, we estimate multinomial logit models for each study period. This model derives from the discrete-choice problem facing each independent hospital *h* at the start of the period: select the outcome *k* that maximizes its objective function. The objective function (denoted here by *U*) is assumed to be a linear combination of relevant covariates:

$$U_{hk} = \beta_k \mathrm{RTU}_h + \gamma_k \text{residual profits}_h + v_k' \boldsymbol{X}_h + e_h, \tag{2}$$

where *h* denotes hospital, $k \in$ {stay independent, join for-profit system, join nonprofit system, exit, merge}, and $\boldsymbol{X}_h$ is the vector of hospital and market characteristics described above. Assuming the errors are drawn independently from a type I extreme-value distribution, we can estimate the difference in the parameters for each *k* relative to a given baseline option (for example, $\beta_{\text{join for-profit system}} - \beta_{\text{stay independent}}$); exponentiating these coefficients gives the relative risk ratios associated with a 1-unit change in each predictor. Relative risk ratios below 1 imply that increases in the predictor reduce the likehood of the outcome in question relative to the base outcome, ceteris paribus.

The explanatory variables of interest are RTU and residual profits, which measure the profits to be gained by regulatory exploitation and increased operating efficiency, respectively. While RTU and residual profits are theoretically correlated, in practice the correlation coefficient never exceeds .07 in absolute value in any year. We also report relative risk ratios for the ownership status of the hospital at the start of the study period. The descriptive statistics suggest that hospitals are more likely to affiliate with systems of the same ownership status (with the exception of government hospitals, as few government-owned systems exist).

Model 1 in Table 5 presents the relative risk ratios associated with these key variables for each outcome during the treatment period, 1988–92. Higher RTU hospitals are more likely ($p < .10$) to join for-profit systems (relative to remaining independent) and less likely ($p < .05$) to exit. The relative risk ratios associated with residual profits are all less than one (and highly significant for joining nonprofit systems and exiting), implying that profitable hospitals are most likely to remain independent, ceteris paribus. Owing to measurement error in RTU and residual profits, all coefficient estimates on these variables are conservative

[20] The nine regions (as defined by the American Hospital Association) are New England, Mid-Atlantic, South Atlantic, East North Central, East South Central, West North Central, West South Central, Mountain, and Pacific.

**Table 5**

**Risk of New Affiliations, Treatment Period (1988–92)**

| | Join For-Profit System | Join Nonprofit System | Exit | Merge |
|---|---|---|---|---|
| Model 1: | | | | |
| RTU | 1.083$^{+}$ | 1.034 | .863* | 1.018 |
| | (.050) | (.057) | (.051) | (.068) |
| Residual profit | .977 | .956** | .964** | .975 |
| | (.014) | (.014) | (.014) | (.019) |
| For profit | 1.264 | . . . | 1.752 | 3.057$^{+}$ |
| | (.734) | | (.812) | (1.966) |
| Government | .800 | .868 | .404* | .974 |
| | (.232) | (.268) | (.150) | (.423) |
| Model 2: | | | | |
| RTU quintiles: | | | | |
| 2 | 1.572 | 1.181 | .476$^{+}$ | .709 |
| | (.622) | (.544) | (.191) | (.331) |
| 3 | 1.539 | 1.813 | .552 | .857 |
| | (.640) | (.783) | (.228) | (.392) |
| 4 | .981 | 1.854 | .345* | .942 |
| | (.454) | (.805) | (.163) | (.444) |
| 5 | 2.287* | 1.459 | .401* | .923 |
| | (.904) | (.682) | (.175) | (.467) |
| Residual profit quintiles: | | | | |
| 2 | 1.071 | .546 | .452$^{+}$ | 1.321 |
| | (.399) | (.212) | (.198) | (.553) |
| 3 | 1.013 | .500$^{+}$ | .194** | 1.222 |
| | (.374) | (.194) | (.109) | (.514) |
| 4 | .785 | .582 | .349* | .372 |
| | (.300) | (.210) | (.153) | (.225) |
| 5 | .466$^{+}$ | .279** | .437* | .457 |
| | (.194) | (.128) | (.158) | (.277) |
| For profit | 1.369 | . . . | 1.72 | 3.096 |
| | (.803) | | (.797) | (2.012) |
| Government | .854 | .875 | .406* | 1.117 |
| | (.251) | (.273) | (.150) | (.495) |
| Sample probabilities | .032 | .029 | .026 | .022 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 1 | .022 | .020 | .044 | .025 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 5 | .049 | .029 | .019 | .023 |

**Note.** Values are relative risk ratios from multinomial logit model of affiliation decisions. The base outcome is "stay independent." A relative risk ratio less (greater) than 1 implies the covariate is associated with a lower (higher) risk of the outcome relative to the base outcome. Standard errors are in parentheses. $N = 2{,}320$.

$^{+}$ $p < .10$.

* $p < .05$.

** $p < .01$.

(that is, the coefficient estimates suffer from attenuation bias). The results also confirm two patterns evident in the raw (that is, unadjusted) affiliation data in Table 3: government hospitals are least likely to exit, and for-profit hospitals are most likely to merge.

In model 2, we consider the possibility that the relationships of interest are nonlinear by including dummies for quintiles of RTU and residual profits in place of the continuous measures. This specification reveals that only hospitals with exceptionally high RTU (the top quintile) are significantly more likely to join for-profit systems ($p < .05$). Hospitals with exceptionally low RTU (the omitted bottom quintile) are significantly more likely to exit. The RTU quintile is not significantly associated with the probabilities of the other outcomes. The point estimates are consistent with the hypothesis that high RTU has a greater impact on for-profit than nonprofit affiliation, although we cannot reject equality of the for-profit and nonprofit coefficients.

To help interpret these results, we calculate the change in the predicted probabilities of each outcome when hospitals are shifted from the bottom to the top quintile of RTU. The results of this exercise, reported beneath the relative risk ratios from model 2, indicate that the probability of joining a for-profit system more than doubles as a result of this shift, while the probability of exit more than halves.

Model 2 also reveals some nonlinearities in the impact of profitability on outcomes. Hospitals in the top quintile of profitability are unlikely to affiliate with systems or to exit, while those in the bottom quintile are likeliest to exit, ceteris paribus.

As a check on our identification strategy, Table 6 presents the results of models 1 and 2 using data from the pretreatment period, 1984–87. The explanatory variable of interest is 1988 RTU. If 1988 RTU does not predict affiliations during the pretreatment period, then we can rule out the possibility that hospitals with high post-reform RTU were always attractive targets for systems (presumably because of some omitted, but correlated, factor). Of course, it remains possible, if unlikely, that hospitals with high post-reform RTU suddenly became attractive in 1988 because one of these omitted factors also changed then. The other explanatory variables for the pretreatment-period analysis are measured as of the base year (1984) or the earliest available year (given in Table 4). Note that no hospitals in the sample merged during this period, and we drop from the sample the one hospital that exited.[21]

The results offer no support for the omitted-variables hypothesis. The term RTU is not significantly associated with system affiliation of either ownership type during the pretreatment period, and the point estimates suggest that hospitals in high-RTU quintiles are more likely to affiliate with nonprofit than for-

[21] Of the 2,616 independent hospitals in 1984, 42 are dropped from the estimation sample because they lack RTU in 1988. Of these 42, 34 exited by 1988 (though only one by 1987), and eight had missing data.

Table 6

**Risk of New Affiliations, Pretreatment Period (1984–87)**

| | Join For-Profit System | Join Nonprofit System |
|---|---|---|
| Model 1: | | |
| 1988 RTU | .970 | 1.033 |
| | (.034) | (.038) |
| Residual profit | .959** | .953** |
| | (.011) | (.011) |
| For profit | 4.678** | . . . |
| | (1.726) | |
| Government | 1.024 | .703 |
| | (.229) | (.160) |
| Model 2: | | |
| 1988 RTU quintiles: | | |
| 2 | 1.299 | 1.148 |
| | (.354) | (.358) |
| 3 | 1.149 | 1.276 |
| | (.332) | (.395) |
| 4 | .934 | 1.317 |
| | (.276) | (.404) |
| 5 | .657 | 1.256 |
| | (.202) | (.383) |
| Residual profit quintiles: | | |
| 2 | .677 | 1.089 |
| | (.188) | (.275) |
| 3 | .571* | .512* |
| | (.163) | (.148) |
| 4 | .458** | .289** |
| | (.131) | (.097) |
| 5 | .399** | .352** |
| | (.111) | (.104) |
| For profit | 4.739** | .278$^{+}$ |
| | (1.768) | (.210) |
| Government | 1.024 | .703 |
| | (.229) | (.162) |
| Sample probabilities | .052 | .051 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 1 | .053 | .044 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 5 | .036 | .055 |

**Note.** Values are relative risk ratios from multinomial logit models of affiliation decisions. The base outcome is "stay independent." RTU is measured as of 1988, hence exit is not possible for hospitals in this sample. A relative risk ratio less (greater) than 1 implies that the covariate is associated with a lower (higher) risk of the outcome relative to the base outcome. Standard errors are in parentheses. $N = 2{,}574$ (which differs from the 2,616 reported in Table 2 because 42 hospitals lack RTU data in 1988; 34 of these 42 had exited by 1988).

$^{+}$ $p < .10$.

$^{*}$ $p < .05$.

$^{**}$ $p < .01$.

profit systems during the pretreatment period (a one-sided $t$-test rejects for-profit[RTU quintile 5] > nonprofit[RTU quintile 5] at $p = .06$). Although the rate of system affiliation is much higher during the pretreatment period, suggesting differences in aggregate patterns between the two periods, it is difficult to develop an alternative explanation for why the hospitals with the highest RTUs suddenly became more likely to affiliate with for-profit systems after 1988, when they were not more likely to do so in prior years. By contrast, operating profits are an even stronger predictor of system affiliation during the pretreatment period, with hospitals in quintiles 3, 4, and 5 of profitability significantly more likely to remain independent.

Last, Table 7 presents results for the posttreatment period, 1992–96. As expected, RTU is no longer significantly associated with the propensity to join a system. Profits continue to be associated with a reduced propensity to join for-profit systems and to exit, but they are not predictive with respect to new nonprofit system affiliations. Abbreviating the posttreatment period by 1 year (that is, using 1993–96) has little impact on these findings, and the results in the longer treatment period (1988–93) are also quite similar.

### *5.2. Effect of System Affiliation on Upcoding*

In this section, we examine whether newly affiliated hospitals increased their upcoding more than a matched sample of independent hospitals. For this analysis, the outcome measure is the change in RTU over a 4-year period spanning the year before affiliation to 3 years after, that is, $\mathrm{RTU}_{hjr,t(a)+3} - \mathrm{RTU}_{hjr,t(a)-1}$. We perform separate analyses for new nonprofit system affiliates and new for-profit system affiliates. For example, for the for-profit affiliation analyses, we begin by estimating a probit model for new for-profit affiliations in year $t$. We use the results of this model to calculate propensity scores for each hospital in year $t$. Each affiliating hospital is matched to $n$ control hospitals using the "nearest neighbor" matching algorithm by Leuven and Sienesi (2003). This algorithm selects matches with the nearest propensity score to that of each treatment hospital, subject to the requirement that the covariates are roughly similar (balanced) (see Leuven and Sienesi 2003).[22] The identifying assumption is that RTU in the treatment group would have changed by the same amount as in the matched sample had these hospitals remained independent. Because aggregate changes in RTU differ over time, we match hospitals affiliating in year $t(a)$ with controls in year $t(a)$.

Table 8 presents estimates of the average treatment effect (on the treated) of joining a for-profit system or a nonprofit system. Standard errors are adjusted

[22] We perform the matching separately by year in order to obtain control hospitals with RTU changes over the same time period as each treatment hospital (that is, hospitals joining a system in 1990 are matched to control hospitals in 1990), so that the change in RTU for both treatment and matched units is measured over 1989 to 1993.

**Table 7**
**Risk of New Affiliations, Posttreatment Period (1992–96)**

| | Join For-Profit System | Join Nonprofit System | Exit | Merge |
|---|---|---|---|---|
| Model 1: | | | | |
| RTU | .994 | .935$^{+}$ | .976 | 1.090 |
| | (.044) | (.037) | (.086) | (.069) |
| Residual profit | .961** | .999 | .911** | .973 |
| | (.106) | (.011) | (.018) | (.019) |
| For profit | 2.794** | .514 | 2.641$^{+}$ | 1.328 |
| | (.944) | (.225) | (1.388) | (.804) |
| Government | .992 | .684$^{+}$ | .476 | .711 |
| | .224) | (.139) | (.252) | .296) |
| Model 2: | | | | |
| RTU quintiles: | | | | |
| 2 | 1.099 | 1.081 | .712 | 1.168 |
| | (.321) | (.254) | (.387) | (.531) |
| 3 | 1.310 | .902 | .469 | 2.082$^{+}$ |
| | (.384) | (.221) | (.294) | (.870) |
| 4 | 1.132 | .770 | .692 | 2.245$^{+}$ |
| | (.350) | (.195) | (.415) | (.935) |
| 5 | .947 | .741 | 1.122 | 1.441 |
| | (.297) | (.191) | (.619) | (.681) |
| Residual profit quintiles: | | | | |
| 2 | .994 | 1.321 | .385$^{+}$ | .573 |
| | (.267) | (.322) | (.202) | (.230) |
| 3 | .548* | .974 | .188** | .735 |
| | (.164) | (.248) | (.113) | (.274) |
| 4 | .443** | 1.211 | .138** | .702 |
| | (.137) | (.290) | (.092) | (.270) |
| 5 | .429** | .673 | .162** | .658 |
| | (.122) | (.185) | (.089) | (.297) |
| For profit | 2.723** | .512 | 2.483$^{+}$ | 1.359 |
| | (.927) | (.226) | (1.297) | (.823) |
| Government | 1.051 | .713 | .482 | .715 |
| | (.242) | (.147) | (.258) | (.300) |
| Sample probabilities | .065 | .094 | .018 | .035 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 1 | .056 | .104 | .022 | .023 |
| Predicted probabilities if all hospitals are assigned to RTU quintile 5 | .054 | .080 | .025 | .033 |

**Note.** Values are relative risk ratios from multinomial logit model of affiliation decisions. The base outcome is "stay independent." A relative risk ratio less (greater) than 1 implies the covariate is associated with a lower (higher) risk of the outcome relative to the base outcome. Standard errors are in parentheses. $N = 2{,}214$.

$^{+}$ $p < .10$.

* $p < .05$.

** $p < .01$.

Table 8

Change in Room to Upcode following System Affiliation

| | For-Profit System | | Nonprofit System | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Average treatment effect | −1.392** | −1.209** | −.138 | −.016 |
| | (.477) | (.463) | (.444) | (.423) |
| Matches per treatment hospital | 3 | 5 | 3 | 5 |
| Observations | 224 | 321 | 229 | 324 |
| Mean (SD) of dependent variable | −2.216 | −2.308 | -1.700 | −1.761 |
| | (3.151) | (3.207) | (2.853) | (2.968) |

**Note.** The dependent variable is the change in RTU over a 4-year period spanning the year before affiliation, $t(a)$, to 3 years after; that is, $\mathrm{RTU}_{hjr,t(a)+3} - \mathrm{RTU}_{hjr,t(a)-1}$. Matches are drawn with replacement, hence some control hospitals may match to more than one treatment hospital; these hospitals are weighted accordingly. The number of treatment hospitals (60 in for-profit systems and 67 in nonprofit systems) is smaller than that reported in Table 3 because of missing data for the dependent variable.

** $p < .01$.

to reflect the weights assigned to each treatment hospital match.[23] The results indicate that hospitals joining for-profit systems decreased their RTU significantly more than the matched samples of hospitals that remained independent. By comparison, the effect on RTU of joining a nonprofit system is small and imprecisely estimated. Two-sided $t$-tests reject equality of the for-profit and nonprofit estimates at $p < .06$.

The estimated treatment effect (based solely on this decrease in RTU) is approximately 1 percent of Medicare inpatient revenues, or roughly $67,000 per treatment hospital per year. Given that 71 percent of hospitals in the treatment group had negative operating profits during the base year of 1988, and the median figure among hospitals with positive profits was only $280,000, this is a nontrivial amount.[24] More important, the total amount to be gained via aggressive exploitation of all regulatory loopholes is likely to be several multiples of $67,000, as there are myriad other ways to upcode inpatient and outpatient visits for Medicare and non-Medicare patients, as well as similar opportunities in a variety of other areas (for example, excessive charges to trigger extra outlier payments by Medicare). The RTU is but a small piece of the pie available to managers willing and able to exploit loopholes.

## 6. Conclusion

Firms in regulated industries often have opportunities to enhance profits by taking advantage of regulatory loopholes. Managers who fail to exploit these

[23] The outcomes are assumed to be independent across observations, yielding Var (average treatment effect) $= 1/(N^{\mathrm{T}})^2\,[\sum_{i\in \mathrm{T}} \mathrm{Var}\,(Y_i^{\mathrm{T}}) + \sum_{j\in \mathrm{C}} (w_j)^2\,\mathrm{Var}\,(Y_j^{\mathrm{C}})]$, where T denotes treatment, C denotes control, $w_j$ is the weight assigned to a particular observation in the control group, and $Y$ is the change in RTU. For details, see Becker and Ichino (2002). Matching is done with replacement, so weights can exceed $\frac{1}{3}$ ($\frac{1}{5}$) for the three-match (five-match) control group.

[24] Figures were converted from 1988 to 2000 dollars using the CPI-U. The amount $67,000 is 1 percent of mean inpatient Medicare revenues in the treatment group.

opportunities, whether by choice or by oversight, risk replacement by new managers who are willing and able to extract these rents. The 1988 change in Medicare's payment rates to hospitals created a natural experiment for testing whether the market for corporate control functions as predicted in this setting.

Following the reform, hospitals could increase their revenues significantly by upcoding in patient charts. Dafny (2005) previously showed that for-profit hospitals exploited this opportunity to a greater extent than did their nonprofit or government-owned peers. In this paper, we find evidence that for-profit systems took over the management of hospitals with particularly large opportunities for upcoding in the wake of the payment change. This behavior was not apparent before the change and was abandoned a few years later, after regulators, academics, and the press began exposing upcoding-related fraud. After assuming management responsibilities, for-profit systems significantly increased the extent of upcoding.

One interesting observation is that most nonprofit hospitals joining for-profit systems keep ownership of their assets; that is, they choose contractual management relationships with these systems. This allows hospital owners to retain strategic direction over their facilities and therefore may be more palatable for various community stakeholders than an outright sale of assets.[25] This phenomenon may contribute to the perception that nonprofit hospitals are "for profits in disguise" (Weisbrod 1988, p. 11).

Owners of struggling hospitals have other options besides outsourcing management; a less drastic step would be to replace the hospital chief executive officer (CEO). Although we lack the data to see whether RTU is associated with greater CEO turnover during the treatment period, such a pattern would be consistent with our findings. In general, financial distress does appear to associated with CEO turnover (Brickley and Van Horn 2002).[26]

As envisioned by Manne (1965), the market for corporate control is a mechanism for welfare improvement: new managers generate greater rents than those they replace. Our case study of the U.S. hospital industry suggests that this mechanism may be welfare reducing in some settings. Although owners of hospitals with formerly low rates of upcoding enjoyed substantial increases in revenues after replacing their managers, it is difficult to argue that this upcoding improved social welfare. Medical records became tainted with misleading information, hospital reimbursement rates were altered to reflect these inaccuracies, hospitals deployed additional resources to manipulate diagnostic codes, and regulators deployed resources to monitor them. Clearly, the market for corporate control may not always be "desirable from a general welfare-economics point of view."

[25] We thank the anonymous referee for this observation.

[26] The absence of a relationship between RTU and chief executive officer (CEO) turnover would not be inconsistent with our results, however, because replacing the CEO may not be sufficient to trigger a change in upcoding (which typically requires information technology and personnel investments).

# Appendix

## Methods

### *Identifying New System Affiliations*

This Appendix describes problems with the system identification (ID) codes in the AHA data and the steps we took to remedy them.

1. Many hospitals are recorded as members of a system in years $t$ and $t + 2$ but not in year $t + 1$; we do not consider such hospitals to be independent in $t + 1$. In most such cases, the system code is the same in $t$ and $t + 2$. Because system code numbers can change from one year to the next, we do not assume that a different code in $t + 2$ reflects a change in affiliation. We performed extensive research for a random sample of 10 such hospitals and found no evidence of a system change during the relevant time period.

2. When the gap between system and ID is 2 years in duration, we consistently replaced these IDs with the prior system ID number only if the system ID is the same in $t$ and $t + 3$. The 54 cases in which system ID changes after a 2-year gap were researched individually, and changes were made only when supporting evidence was identified. Gaps of 3 years or more were taken to be system changes.

3. To reduce coding error, hospitals in "systems" with only one member are treated as independent. In addition, our analysis of new affiliations is restricted to affiliations with systems of three or more members (this total includes any new members).

We also considered an alternative system identifier generously supplied by Kristin Madison of the University of Pennsylvania Law School. She uses slightly different methods for cleaning the system identifier field; these are described in detail in Madison (2004). She too fills in gaps when hospitals disappear from and reappear into the same system. She adds system ID numbers for systems that are named by hospitals but not recognized by the AHA. The trends in her annual figures for new system affiliations match ours, and the absolute figures are very similar once systems with only two members are excluded.

### *Identifying System Ownership Status*

We used the annual AHA *Guide to Hospitals* (1984–96b) to ascertain ownership status of all systems with 10 or more members and of smaller systems that acquired independent hospitals during any of the study periods. System ownership is assumed to be the same ownership form as the majority of system members in the case of smaller systems that do not acquire independent hospitals during any of the study periods; ties are broken using the *Guides*. Note that these estimates affect only the summary statistics presented in Table 1.

Table A1
Sample Restrictions

| | 1984–87 | 1988–92 | 1992–96 |
|---|---|---|---|
| Hospitals in initial year | 7,110 | 7,037 | 6,732 |
| After excluding: | | | |
| Nongeneral service | 6,025 | 5,770 | 5,434 |
| State or federal | 5,613 | 5,361 | 5,047 |
| Located in U.S. territories | 5,566 | 5,313 | 5,008 |
| System members in initial year | 3,521 | 3,144 | 3,011 |
| ≤50 observations in MEDPAR | 2,942 | 2,606 | 2,477 |
| Church operated | 2,808 | 2,485 | 2,369 |
| ≤30 beds | 2,674 | 2,367 | 2,219 |
| Missing data in initial year | 2,616 | 2,320 | 2,214 |

**Note.** "Initial year" pertains to the first year of each period. MEDPAR = Medicare Provider Analysis and Review.

## References

Alexander, J. A., and B. L. Lewis. 1984. Hospital Contract Management: A Descriptive Profile. *Health Services Research* 19(4):461–477.

Alexander, J. A., and M. A. Morrisey. 1989. A Resource-Dependent Model of Hospital Contract Management. *Health Services Research* 24(2):259–84.

American Hospital Association. 1984–96a. *Annual Survey of Hospitals.* Chicago: Health Forum.

———. 1984–96b. *Guide to Hospitals.* Chicago: Health Forum.

Andeson, Paul. 1995. Health-Care Fraud Grows; FBI Says Crooks Cost Federal, Private Insurers $44 Billion a Year. *Pittsburgh Post-Gazette*, March 22.

Assaf, Annlouise R., Kate L. Lapane, Joyce L. McKenney, and Richard A. Carleton. 1993. Possible Influence of the Prospective Payment System on the Assignment of Discharge Diagnoses for Coronary Heart Disease. *New England Journal of Medicine* 329(13): 931–35.

Averch, Harvey, and Leland L. Johnson. 1962. Behavior of the Firm under Regulatory Constraints. *American Economic Review* 52(5):1052–69.

Baker, Laurence. 1997. The Effect of HMOs on Fee-for-Service Health Care Expenditures: Evidence from Medicare. *Journal of Health Economics* 16:453–81.

Becker, S. O., and A. Ichino. 2002. Estimation of Average Treatment Effects Based on Propensity Scores. *Stata Journal* 2(4):358–77.

Brickley, James, and R. Lawrence Van Horn. 2002. Managerial Incentives in Nonprofit Organizations: Evidence from Hospitals. *Journal of Law and Economics* 45:227–50.

Cuellar, Allison Evans., and Paul J. Gertler. 2005. How the Expansion of Hospital Systems Has Affected Consumers. *Health Affairs* 24(1):213–20.

Cutler, David M. 1995. The Incidence of Adverse Medical Outcomes under Prospective Payment. *Econometrica* 63:29–50.

Dafny, Leemore S. 2005. How Do Hospitals Respond to Price Changes? *American Economic Review* 95:1525–47.

Desai, Mihir A., and James R. Hines, Jr. 2002. Expectations and Expatriations: Tracing the Causes and Consequences of Corporate Inversions. *National Tax Journal* 55(3): 409–40.

Dranove, David. 1988. Pricing by Non-profit Institutions: The Case of Hospital Cost Shifting. *Journal of Health Economics* 7(1):47–57.

Duggan, Mark, and Fiona M. Scott Morton. 2006. The Distortionary Effects of Government Procurement: Evidence from Medicaid Prescription Drug Purchasing. *Quarterly Journal of Economics* 121:1–31.

Eichenwald, Kurt. 2000. Big Hospital Manager to Pay a Fraud Settlement of $95 Million. *New York Times,* October 3.

Glaeser, Edward L., David I. Laibson, José A. Scheinkman, and Christine L. Soutter. 2000. Measuring Trust. *Quarterly Journal of Economics* 115:811–46.

Golden, D., and S. Kurkjian. 1994. The Fraud Factor: Hidden Costs of Health Care. *Boston Globe*, July 31.

Goolsbee, Austan. 2000. What Happens When You Tax the Rich? Evidence from Executive Compensation. *Journal of Political Economy* 108:352–78.

Hall, Brian J., and Jeffrey B. Liebman. 2000. The Taxation of Executive Compensation. Pp. 1–44 in vol. 14 of *Tax Policy and the Economy,* edited by James M. Poterba. Cambridge, Mass.: MIT Press.

Horwitz, Jill R. 2005. Making Profits and Providing Care: Comparing Nonprofit, For-Profit and Government Hospitals. *Health Affairs* 24(3):790–801.

Kyle, Margaret K. 2007. Pharmaceutical Price Controls and Entry Strategies. *Review of Economics and Statistics* 89:88–99.

Lagnado, Lucette. 1997. Columbia/HCA Graded Its Hospitals on Severity of Their Medicare Claims. *Wall Street Journal,* May 30.

Leuven, Edwin, and Barbara Siensi. 2003. PSMATCH 2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing. Version 3.0.0. Boston College, Department of Economics, Boston.

Lipman, L. 1995. FBI Chief: Health-Care Fraud Endemic. *Denver Post,* March 22.

Madison, Kristin. 2004. Multihospital System Membership and Patient Treatments, Expenditures, and Outcomes. *Health Services Research* 39:749–69.

Manne, Henry G. 1965. Mergers and the Market for Corporate Control. *Journal of Political Economy* 73:110–20.

McCue, Michael J., and Jan P. Clement. 1992. Characteristics of Divested HCA and AMI Hospitals. *Medical Care* 30(4):360–72.

Mobley, Lee R. 1997. Multihospital Chain Acquisitions and Competition in Local Health Care Markets. *Review of Industrial Organization* 12(2):185–202.

*Modern Healthcare*. 1990. Quorum Health Forms New Turnaround Business. October 8, p. 7.

O'Harrow, Robert, Jr. 2002. HCA, U.S. Agree to Fraud Settlement. *Washington Post,* December 19.

Roomkin, Myron J., and Burton A. Weisbrod. 1999. Managerial Compensation and Incentives in For-profit and Nonprofit Hospitals. *Journal of Law, Economics, and Organization* 15:750–81.

Rose, Nancy L., and Catherine Wolfram. 2002 Regulating Executive Pay: Using the Tax Code to Influence CEO Compensation. *Journal of Labor Economics* 20 (2):S138-S175.

Rundle, Rhonda. 2006. Tenet CEO Tries to Erase Effects of Scandals. *Wall Street Journal,* July 3.

Silverman, Elaine, and Jonathan Skinner. 2004. Medicare Upcoding and Hospital Ownership. *Journal of Health Economics* 23(2):369–90.

Thomas, Pierre. 1994. Psychiatric Hospital Group to Pay Record Fine. *Washington Post,* June 30.

U.S. Department of Health and Human Services. 1998. Using Software to Detect Upcoding of Hospital Bills. Report OEI-01–97-00100. Office of Inspector General, Boston.

———. 1999. Medicare Payments for Septicemia. Report OEI-03–98-00370. Office of Inspector General, Philadelphia.

———. 2001. Medicare Hospital Prospective Payment System: How DRG Rates Are Calculated and Updated. Report OEI-09–00-00200. Office of Inspector General, San Francisco.

Weisbrod, Burton A. 1988. *The Nonprofit Economy.* Cambridge, Mass.: Harvard University Press.

Winter, Ariel, and Julian Pettengill. 2003. Relationships among Medicare Inpatient, Overall Medicare and Total Margins for Hospitals. Report to the Medicare Payment Advisory Commission, Washington, D.C.