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REGULATORY EXPLOITATION AND THE
MARKET FOR CORPORATE CONTROL

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ABSTRACT

This paper investigates whether managers who fail to exploit regulatory loopholes are vulnerable to replacement. We use the U.S. hospital industry in 1985-1996 as a case study. A 1988 change in Medicare rules widened a pre-existing loophole in the Medicare payment system, presenting hospitals with an opportunity to increase operating margins by five or more percentage points simply by “upcoding” patients to more lucrative codes. We find that “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 that hospitals replacing their management subsequently upcode more than a sample of similar hospitals that did not, as identified by propensity scores.

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1. Introduction

When the market for corporate control is efficient, owners or managers who “leave money on the table” will be replaced. Whether such ousters (or the threat thereof) increase social welfare clearly depends on the source of unrealized profits. In this paper, we examine changes in corporate control resulting from managers’ 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. We find empirical evidence for such managerial changes using panel data on the U.S. hospital industry between 1985 and 1996.

The U.S. hospital industry is highly regulated at both the state and federal level, 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 widened a pre-existing loophole in the system, presenting hospitals with an opportunity to increase operating margins by five percentage points simply by reclassifying patients to more lucrative codes, a practice known as “upcoding.” Given typical operating margins of less than two percentage points during this time period, this is a substantial figure.

The exact amount of the potential increase in Medicare payments depends on the mix of patients in each hospital and the extent to which the hospital was exploiting the loophole prior to the regulatory change. 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 dramatically larger 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 greater RTU following the 1988 reform were more likely to switch to management by for-profit systems.¹

We compare the predictors of joining a for-profit system in 1985-1987 (the “pre-period”), 1989-1992 (the “treatment” period), and 1993-1996 (the “post period”, during which there was a massive federal crackdown on Medicare fraud).² In addition to RTU, we also examine whether poor operating performance precipitates a switch to for-profit system management. We contrast our findings with the predictors of joining a nonprofit system during each of these periods.

We obtain three main results: (1) during the period immediately following the implementation of the new Medicare rules, RTU was a statistically and economically significant predictor of whether an independent hospital joined a for-profit system; (2) hospitals that joined for-profit systems during this period subsequently increased their upcoding relative to a matched sample of similar hospitals that did not join for-profit systems; and (3) RTU is not associated with joining a for-profit system before 1988 or after 1992, nor with joining a nonprofit system at any time.

Our results suggest that a well-functioning market for corporate control intensifies the agency problems that arise between regulators and the firms they regulate. In this setting, Medicare is a principal acting on behalf of an insured population, and hospitals serve as Medicare’s agents. Medicare bases payments on diagnostic conditions, and these rules are enforced in a second-best world: hospitals must report diagnostic information that is to some

¹ As we discuss below, most hospitals joining for-profit systems were not acquired outright; rather, these hospitals outsourced the management function to for-profit “contract management organizations.”

² The “pre period” is one year shorter than the other periods because the data are not available prior to 1985.

extent unverifiable.³ As might be expected, some hospitals take greater advantage of the discretion afforded them. We find that the market for corporate control led to managerial changes at hospitals that did not avail themselves of the ability to exploit their informational advantage. This situation is akin to that described in Shleifer and Summers (1988), in which hostile takeovers magnify agency problems arising from the inability of firms to commit to honor implicit contracts with their agents (i.e. a mutual “understanding” that the firm will provide lifelong employment in exchange for upfront relationship-specific investments by employees).

To set the stage for our analysis, the following section describes the structure of the U.S. hospital industry, the formation of hospital systems, and prior related research. 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

A. 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 consolidation into hospital “systems.” A system consists of a group of affiliated hospitals that identify themselves as such to the American Hospital Association. Systems can bring considerable expertise to hospitals in the areas of labor management, marketing, and

³For a more detailed discussion of the incentive problems arising from unverifiable treatment, see Ma and McGuire (1997).

information technology, including processes and software used for diagnostic coding. Some functions may be consolidated across member hospitals. Systems may also provide increased access to capital, and negotiate joint contracts with suppliers and insurers.

“Contract management organizations” (CMOs) are an important class of systems. CMOs are for-profit companies that specialize in managing hospitals.⁴ They offer many of the same benefits to hospitals as do other systems, but they do not negotiate joint prices with insurers. Hospital boards seeking to improve performance while maintaining asset ownership can outsource day-to-day management functions to CMOs. In the time period that we study, the vast majority of independent hospitals joining for-profit systems opted for contract management.

If a hospital agrees to join a CMO, there must be some expectation that the partnership will add value; that is, that the CMO will boost hospital revenues beyond the additional management costs. According to industry publications, CMOs specifically targeted financially-distressed hospitals during this time period.⁵ Hence, we include a measure of operating margins as a predictor in our analysis of system membership. Hospitals that do not fully exploit regulatory loopholes may also be attractive targets for CMOs, as exploiting such loopholes can quickly improve a balance sheet. This is the hypothesis we test explicitly in our empirical analysis.

Table 1 gives the number of community hospitals and their system affiliations in 1984 and 1996.⁶ During this period, system affiliation increased from 37 to 46 percent. Table 2

⁴ Some of these systems consist of contract-managed as well as wholly-owned hospitals.

⁵ For example, see “Quorum Health Forms New Turnaround Business,” 10/8/1990, *Modern Healthcare*.

⁶ See Data Appendix for a description of how system membership and ownership is determined using data from the *American Hospital Association*.

provides additional detail on new affiliations by hospitals that were independent in 1984.⁷ Our empirical analysis focuses on the decisions of *independent* hospitals to join hospital systems, as this decision is distinct from the decision to change system affiliation, and occurs much more frequently in the data.⁸ Of 3,521 independent community hospitals in the United States in 1984, 725 became part of a hospital system by 1996. These hospitals came from all ownership types, while systems tended to be privately-owned.

Although our study focuses on the predictors of *individual* system affiliations, the extensive literature on aggregate system formation informs our analysis and helps to frame the findings. Dranove and Lindrooth (2003) and Connor et al (1997) find that integration into multi-hospital systems has no impact on hospital costs. 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 Morrissey (1989) and Alexander and Lewis (1984) find that smaller hospitals and hospitals with weak financial performance are likeliest to join CMOs. Finally, Mobley (1997) documents that nonprofit systems tend to consist of multiple hospitals in a local market area, while for-profits have broader geographic spread. These patterns suggest that nonprofit and for-profit integration strategies differ, a prediction that is corroborated by our findings.

⁷ Some hospitals may have changed affiliations more than once during this time period. These figures represent system status as of 1984 and 1986.

⁸ We observe few system changes in our data, and due to mergers and changes in system identification numbers, even these changes may not be accurate. We therefore lose little information by focusing on the initial decision to affiliate with a system.

B. Gaming Governmental Regulations

To our knowledge, there are no prior studies examining regulatory exploitation as a motive for managerial changes, nor are there systematic evaluations of ousters to eliminate “X inefficiency” more generally.⁹ 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 (2005) and Kyle (2005) 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 Leibman (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.

In addition to the short-term impact on government revenues, there are long-term economic implications of this phenomenon. These implications, which arise due to the principal-agent problem between Medicare and hospitals, are well-illustrated by Shleifer and Summers (1988) in the context of hostile takeovers. The authors point out that a corporate raider might acquire a firm that has made implicit contracts with its stakeholders. In particular, those contracts might call for the stakeholders to make specific investments upfront in exchange for compensation at a later time. Such contracts may be optimal for both parties *ex ante*, but after the stakeholders have made their specific investments it is more profitable for the firm to renege on the contracts. If current managers are reluctant to do so, the market for corporate control may replace them.

⁹ “X inefficiency,” a term coined by Leibenstein (1966), refers to a phenomenon in which firms with similar inputs and technology achieve different levels of output.

Violations of implicit contracts clearly weaken the ability of firms to rely upon them to achieve superior outcomes. This problem is analogous to that faced by Medicare regulators, whose implicit contracts with hospitals are apparent in the constant “give and take” between the parties. Hospitals are expected to comply with myriad, onerous regulations (often requiring upfront investments), despite a minimal budget devoted to enforcement. In turn, hospitals have an active voice in the regulatory process, and their interests are frequently cited as factors in Medicare decisions. For example, the annual modifications to Medicare’s Prospective Payment System are always introduced as a “proposed rule” three months prior to implementation. Hospitals are invited to comment on the proposal, and Medicare carefully considers and responds publicly to these comments before finalizing the rule. The published dialogue (reproduced in the *Federal Register*) clearly reflects Medicare’s objective of promoting the financial solvency of hospitals.

3. Room to Upcode: A Measure of Foregone 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.

A. 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 (i.e. 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

$$(1) \quad P_{hd} = P_h \cdot (1 + IME_h) \cdot (1 + DSH_h) \cdot DRG \text{ weight}_d$$

where h indexes hospitals and d indexes DRGs. P_h is a hospital-specific “base payment” amount (inflated annually by a Congressionally-approved “update factor”), IME_h represents a (positive) adjustment factor for indirect medical education (that is, teaching), and DSH_h adjusts payment levels to compensate hospitals with a disproportionate share of indigent patients.¹⁰

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.

¹⁰ This simplified formula appears in Cutler (1995).

Hospitals are responsible for assigning patients to the appropriate DRGs. This system provides a strong incentive to classify patients into the most remunerative DRGs, a practice known as “upcoding.” The term refers to 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 Federal False Claims Act of 1986. Given the breadth of this definition, there are a number of possible reasons hospitals may not upcode maximally.

Upcoding requires careful attention to medical records, sophisticated software, and trained coding personnel. The annual fees charged by independent coding consultants can reach into the millions. Hospital systems may therefore enjoy substantial expertise and economies of scale arising from centralized coding efforts. Where clearly illegal practices are concerned, systems are again likely to have an economic advantage. The extent of upcoding involves a tradeoff that accounts for the expected cost of punishment. A system already engaging in questionable upcoding at one hospital may reason that doing so at additional hospitals will have only an incremental effect on the magnitude of the expected punishment.

Variation in upcoding proclivity may also result from variation in owners’ or managers’ willingness to upcode, and/or differences in the incentives provided to managers to do so. Nonprofit owners and managers may avoid the “gray areas” of upcoding in order to preserve their “trust capital” in the community (Glaeser et al.). 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 towards profits.¹¹ One for-profit hospital chain based managerial bonuses on the coded incidence of complications (Lagnado 1997). Indeed, Silverman and Skinner (2004), as well as Dafny (2005), document greater upcoding among for-profit hospitals.

In addition to the higher costs associated with upcoding, critics contend that patient care may be compromised if hospitals manipulate medical records or alter treatment for the purpose of maximizing reimbursement. Furthermore, Medicare's approach to reining in the costs associated with upcoding – decreasing the annual cost inflation factor applied to all reimbursements – punishes hospitals equally, regardless of the extent to which they upcode and the specific upcoding practices they employ.

B. 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, uncomplicated patients with the same diagnosis. Analyses performed in 1987 revealed that,

¹¹ For example, see “Managerial Compensation and Incentives in For-profit and Nonprofit Hospitals” (Roomkin and Weisbrod 1999), “Managerial Incentives in Nonprofit Organizations: Evidence from Hospitals” (Brickley and Van Horn 2002), and “Making Profits and Providing Care: Comparing Nonprofit, For-Profit, and Government Hospitals” (Horwitz 2005). 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/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.

on average, charges for patients with CC were much higher than charges for patients without CC, but older patients were not significantly more expensive to treat than younger patients (who were primarily aged 65-69). CMS concluded that “in all but a few cases, grouping patients who are over 69 with the CC patients is inappropriate” (52 *Federal Register* 18877), and the agency removed the age qualifiers and recalculated the DRG weights using the new categories.

Table 3 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 (1984-1987). 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 \$2000).¹²

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 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

¹² Table 1A, “National Adjusted Standardized Amounts, Labor/Nonlabor,” Medicare Program; Changes to the Inpatient Hospital Prospective Payment System and Fiscal Year 1988 Rates, 52 *FR* 33034 . \$3,165 is the standardized amount for urban hospitals in 1988. 1988 dollars were converted to 2000 dollars using the CPI-U.

increase in revenues if the initial case-mix index is 1.) We multiply RTU by 100 to facilitate the presentation of our results.

Figure 1a presents annual boxplots of RTU for all general community hospitals in the non-territorial U.S. The large average increase in RTU in 1988 reflects the policy change; the steady decline thereafter reflects the subsequent increase in upcoding. Figure 1b contains RTU boxplots for FP system members only. 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 somewhat smaller (suggesting 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 all hospitals increased from 1.3 in 1987 to 6.3 in 1988, and decreased to 5.7 by 1989, whereas median RTU among FP system members increased from 1.3 in 1987 to 6.0 in 1988 and decreased to 4.8 in 1989.) Boxplots for nonprofit system members are not presented separately, as they are very similar to Figure 1a.

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.) 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 foregoing other similar opportunities.¹³

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 a system. 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.

C. Defining the Treatment Period

Although the 1988 reform substantially heightened the incentive to upcode (and the ability of systems to increase revenues of prospective members via upcoding), 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.¹⁴ The Federal Bureau of Investigation ramped up its health care anti-fraud efforts in 1992; within three years, it nearly tripled the number of agents working exclusively on health

¹³ 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. RTU might therefore serve as an indicator of whether a hospital is taking full advantage of Medicare rules.

¹⁴ Assaf et al., 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): 931-5.

probes.¹⁵ In 1994, Senator William Cohen proposed tougher penalties for health care fraud, citing national research indicating annual costs of as much as \$100 billion.¹⁶ 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.”¹⁷ 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.¹⁸ In 1996, many of his earlier proposals were incorporated into the Health Insurance Portability and Accountability Act that required national standards for health care services and outlines various specific new penalties.¹⁹

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.”²⁰ Beginning in 1995, HCFA 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

¹⁵ Andeson, Paul. “Health-care fraud grows; FBI says crooks cost federal, private insurers \$ 44 billion a year.” *Pittsburgh Post-Gazette*, 3/22/1995, p. A6.

¹⁶ Lipman, L. “FBI Chief: Health-care Fraud Endemic” *Denver Post*, 3/22/1995, p. A13.

¹⁷ Golden, D. and Kurkjian, S. “The Fraud Factor: Hidden Costs of Health Care” *Boston Globe*, 7/31/1994, p. 1.

¹⁸ After a three-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 US history (at the time). See Thomas, Pierre, “Psychiatric Hospital Group to Pay Record Fine” *Washington Post*, 6/30/94, 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, Rhonda, “Tenet CEO Tries to Erase Effects of Scandals,” *Wall Street Journal*, 7/3/06, p. B1, and O’Harrow, Robert Jr. “HCA, U.S. Agree to Fraud Settlement,” *Washington Post*, 12/19/02, p. E01. 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.

¹⁹ Details available in the CMS section of Department of Health and Human Services website (<http://www.cms.hhs.gov/HIPAAGenInfo/>).

²⁰ “Medicare Hospital Prospective Payment System: How DRG Rates Are Calculated and Updated,” DHHS Office of Inspector General (Office of Evaluation and Inspections) OEI-09-00-00200 White Paper, August 2001.

DRGs and hospitals prone to upcoding, and instructed PROs to take actions to eliminate “erroneous billing.”²¹ As of 1996, at least 6 vendors had developed software to help private payers detect upcoding.²² 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 for-profit system membership between 1989 and 1992, immediately after opportunities to upcode Medicare patients increased. We contrast these results with specifications estimated for 1985-1987 (the pre-policy years for which data are available), and 1993-1996.

4. Data

We use the *Annual Survey of Hospitals* conducted by the American Hospital Association (AHA) in 1984-1996 to identify hospitals and system affiliations, and to obtain descriptive characteristics such as number of beds and services provided. RTU for each hospital-year is calculated using the annual DRG weights published in the *Federal Register* and the 20% Medicare Provider Analysis and Review (MEDPAR) dataset for fiscal years 1985-1996. This dataset is a random 20% sample of discharge records (including DRG codes and hospital identifiers) for Medicare hospitalizations. Hospital financial data is obtained from the Health Care Reporting Information Set (HCRIS) for fiscal years 1985-1996, also known as the Medicare Cost Reports. Finally, the Medicare case-mix index, which we use as a

²¹ 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. For example, see “Medicare Payments for Septicemia,” OEI-03-98-00370, March 1999.

²² “Using Software to Detect Upcoding of Hospital Bills,” DHHS Office of Inspector General (Office of Evaluation and Inspections) OEI-01-97-00100 White Paper, August 1998.

control variable, is extracted from the Medicare PPS Impact Files, a hospital-level database of PPS-related variables.

Our sample is restricted to non-federal, non-state, general-service hospitals located in the non-territorial U.S. For each time period we examine, we include only those hospitals that were independent (i.e. unaffiliated with a system) at the start of the time period. The Data Appendix describes our methods for scrubbing 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.²³ 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 1 out of 118 such hospitals joined a for-profit system during the treatment period. Appendix Table 1 lists the number of hospitals excluded by each sample restriction for each of the three time periods.

Table 4 gives the number of hospitals in the study sample for each period, together with the number joining for-profit (FP) or nonprofit (NP) systems during that period.²⁴ We only count affiliations with systems of at least 2 other hospitals; this restriction is irrelevant for FP systems, and is imposed to increase comparability between the FP and NP affiliation results. Affiliation activity for both chain types was much greater during the pre- and post-periods than during the treatment period. These aggregate trends 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. As noted earlier, our objective is not

²³ Approximately 40 percent of Medicare admissions are assigned to DRG pairs, so that 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).

²⁴ Of the 76 hospitals joining FP systems during the treatment period, 44 were nonprofit and 28 were government-owned.

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 5 lists the sources for all independent variables and presents summary statistics as of the start of each study period (the “base” year), except when unavailable in these years (as noted). The independent variables are:

- 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 non-federal, non-state community hospitals in the non-territorial U.S. (i.e. including hospitals that are not independent).²⁵ *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: 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

²⁵ 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-squared for each year is ~.20. Results are available by request.

measured by a count of hi-tech services (cardiac catheterization lab, certified trauma center, computed tomography (CT) scanner, megavoltage radiation therapy and open-heart surgery).

- Market controls: seven dummies for MSA population, county HMO penetration (among the non-elderly), and zipcode demographics (per-capita income and its square, percent black, percent urban).

All specifications include dummies for nine geographic regions identified by the AHA.²⁶

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

A. Effect of RTU on the Probability of System Affiliation

To determine whether hospitals with high RTU are more likely to join hospital systems, we estimate probit models of the following form:

$$(1) \Pr(\text{affiliation})_{hjr} = \Phi(\beta_1 \text{RTU}_{hr} + \beta_2 \text{residual profits}_{hr} + \delta' \omega_r + [\nu' X_{hr}])$$

where h denotes hospital, $j \in \{\text{FP}, \text{NP}\}$, r denotes region, ω_r is a vector of region dummies, and X_h is a vector of hospital and market characteristics that are included in some specifications. We estimate this equation separately for FP and NP system affiliation in

²⁶ 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.

order to compare the predictors of affiliation by ownership type. While there are no unambiguous theoretical predictions regarding the characteristics of hospitals joining the different system types, as discussed earlier, the evidence to date on system affiliation as well as upcoding suggests the patterns will differ. We estimate specification 1 separately for each time period.

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.

Table 6 presents the results of estimating equation 1 for FP system affiliation during the treatment period, 1989-1992. All independent variables are measured as of 1988, the base year (except select control variables, as noted in Table 5). Table 6 presents coefficient estimates and standard errors that have been transformed to reflect the marginal effect of a change in each independent variable on the probability of affiliation, evaluated at the sample means. P-values are determined based on the underlying probit coefficients and associated t-statistics. Column 1 presents estimates excluding the vector of hospital and market controls; these are added in Column 2.

In both models, RTU is associated with an increased propensity to join an FP system. The p-value declines from .07 to .04 when controls are included. A one-standard-deviation increase in RTU is associated with an increase of .005 in the probability of FP system membership. Given the sample mean of .033, this represents an increase of 15 percent. Residual profit is negatively associated with the propensity to join an FP system, and borderline significant in the model with controls ($p=.10$). A one-standard-deviation increase

in residual profits is associated with a decrease of .004 in the probability of joining an FP system. In columns 3 and 4, we consider the possibility that the relationships of interest are non-linear by including dummies for quintiles of the explanatory variables in place of the continuous measures. These specifications reveal that only hospitals with exceptionally high RTU (the top quintile) are significantly more likely to join FP systems. Relative to hospitals with RTU in the bottom quintile, their probability of joining is greater by .029 (without controls) to .024 (with controls). The coefficient estimates in columns 3 and 4 also suggest that independent hospitals with the strongest operating margins are least likely to join FP systems, although this result does not achieve standard levels of statistical significance (p is $\sim .10$ in both specifications).

As a check on our identification strategy, Table 7 presents results for the probability of joining an FP system between 1985 and 1987, using quintiles of the independent variables of interest. These models use RTU from 1988 rather than the base year in order to investigate an alternative explanation for our main result: that omitted factors correlated with high post-reform RTU are driving the increased propensity to join an FP system during the treatment period. If 1988 RTU does not predict affiliations during the pre-period, then we can rule out the possibility that high post-reform RTU hospitals were always attractive targets (presumably due to some omitted, but correlated, factor). Of course, it remains possible, but unlikely, that high post-reform RTU hospitals suddenly became attractive in 1988 because one of these omitted factors also changed then. Other variables are measured as of the base year (1984) or the earliest available year (given in Table 5).

The coefficients in columns 1 and 2 of Table 7 offer no support for this alternative hypothesis. A two-sample t-test rejects equality of the coefficients on the 5th quintile of

RTU for the pre vs. treatment period with $p < .05$ (for both models). Although the rate of system affiliation was much higher during the pre-period, suggesting differences in *aggregate* patterns between the two periods, it is difficult to develop an alternative explanation for why the highest-RTU hospitals suddenly became more likely to affiliate with FP systems after 1988 when they were not more likely to do so in prior years. As expected, RTU is not associated with the propensity to join an FP system during the post period either (columns 3 and 4 of Table 7).

The results in Table 7 also reveal a much stronger relationship between residual profits and the propensity to join an FP system during the pre and post periods as compared to the treatment period. Before and after this window of upcoding opportunity, FP systems appear to have focused their efforts on hospitals in the bottom quintile of operating performance.

Tables 8 and 9 contain estimates from the same specifications as Tables 6 and 7, but the dependent variables are indicators for joining NP systems during the relevant time periods. There is no evidence that hospitals with high RTU were more likely to affiliate with NP systems during any time period. In contrast, financial performance is a driver of affiliation with NP systems during all periods.

To check the robustness of our findings, we estimated our models for each period using a multinomial logit with 3 outcomes: stay independent, affiliate with NP system, affiliate with FP system.²⁷ The results were very similar. We also considered three variations of RTU. First, we multiplied RTU for each hospital by the Medicare share of patients. This measure reflects the relative importance of Medicare upcoding in boosting total inpatient revenues. The coefficients were similar in magnitude, but the estimates were slightly less precise. Second, we estimated the increase in revenues obtainable via upcoding by

²⁷We selected probit models over multinomial logits for ease of interpretation.

multiplying RTU by case-mix-adjusted inpatient Medicare revenues.²⁸ Most of the variation in this measure is due to differences in hospital size rather than RTU, hence the results are different. (In particular, they reflect the fact that the largest hospitals are least likely to affiliate with for-profit systems during all periods.) Finally, all results are robust to the inclusion of state fixed effects.

B. 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 four-year period spanning the year before affiliation, $t(a)$, to 3 years after, i.e. $RTU_{hjr, t(a)+3} - RTU_{hjr, t(a)-1}$. To obtain “matches” to serve as a control group, we calculate propensity scores for each hospital using the richest specification in the previous section (column 4 of Tables 6 and 8). The control groups are selected using the “nearest neighbor” matching algorithm by Leuven and Sienesi (2003), which selects matches with the nearest propensity score to that of each treatment hospital, subject to the requirement that the covariates are roughly similar (“balanced”).²⁹ 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.

²⁸ Ideally, we would use the following formula to estimate the increase in revenues: $RTU \cdot P_h \cdot (1 + IME_h) \cdot (1 + DSH_h) \cdot \text{number of Medicare discharges}$. Unfortunately, the data elements needed to calculate this figure for each hospital are not available in 1985-1988. However, we obtain a very close estimate by using $RTU \cdot (\text{inpatient Medicare revenues}/\text{case-mix index})$. This estimate differs from the first figure because hospitals receive extra payments for exceptionally costly cases (so-called “outlier payments”). The correlation between the two measures is .95 for 1989-1996.

²⁹ See Leuven and Sienesi (2003), “PSMATCH 2: Stata Module to Perform Full Mahalanobis and Propensity Score Matching, Common Support Graphing, and Covariate Imbalance Testing,” version 3.0.0. 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 (i.e. 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 10 presents estimates of the average treatment effect (on the treated) of joining a for-profit system (columns 1 and 2) or a nonprofit system (columns 3 and 4). Columns 1 and 3 present estimates using three matches for each treatment unit; columns 2 and 4 use five matches. Standard errors are adjusted to reflect the weights assigned to each match.³⁰ 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 an NP system is large and *positive*, but imprecisely estimated. Two-sided t-tests easily reject equality of the FP and NP estimates at $p < .05$.

The estimated treatment effect (based solely on this decrease in RTU) is one percent of Medicare inpatient revenues, or approximately \$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.³¹ More importantly, 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

³⁰ The outcomes are assumed to be independent across observations, yielding

$$\text{Var}(\text{average treatment effect}) = \frac{1}{(N^T)^2} \left[\sum_{i \in T} \text{Var}(Y_i^T) + \sum_{j \in C} (w_j)^2 \text{Var}(Y_j^C) \right], \text{ where } T \text{ denotes treatment, } C$$

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 1/3 (1/5) for the 3-match (5-match) control group.

³¹ Figures were converted from 1988 to 2000 dollars using the CPI-U. \$67,000 is one percent of mean inpatient Medicare revenues in the treatment group.

areas (e.g. excessive charges to trigger extra “outlier payments” by Medicare). 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 face opportunities to enhance profits by taking advantage of regulatory loopholes. Managers who overlook these opportunities, either by choice or because they lack the requisite capabilities to exploit them, risk replacement by executive teams who are willing and able to seek these rents. Medicare’s 1988 reform to hospital payment rates created a natural experiment for testing whether the market for corporate control functions in this manner.

Following the reform, hospitals could increase their revenues by several percentage points by engaging in systematic upcoding of patient charts. Dafny (2005) illustrates that for-profit *hospitals* exploited this opportunity to a greater extent than their nonprofit or government-owned peers. We find evidence suggesting that for-profit *systems* obtained new nonprofit and government-owned members with particularly large opportunities for upcoding. This behavior was not apparent before the payment change, and was abandoned a few years later, after regulators, academics, and the press began exposing upcoding-related fraud.

Despite the windfall gains available through upcoding, at no time was nonprofit system membership associated with room to upcode. These results suggest that researchers studying nonprofit vs. for-profit institutions must look closely at the ownership type of vendors to whom many services are outsourced. Our findings also suggest the market for corporate control may impede not only the enforcement but also the design of regulations.

Managerial takeovers may inhibit the ability of regulators to rely upon implicit contracts with their agents to achieve the most efficient outcomes.

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

Year	Independent	NP System	FP System	GOV System	Total
1984	3521	1081	917	47	5566
%	63%	19%	16%	1%	100%
1996	2621	1248	896	46	4811
%	54%	26%	19%	1%	100%

Note: Sample excludes federal and state hospitals and hospitals located in U.S. territories.

Table 2: New Affiliations by Ownership Status of Hospital and System, 1984-1996

	NP System		FP System		GOV System	
NP Hospital	367	83%	93	35%	4	22%
GOV Hospital	72	16%	91	34%	14	88%
FP Hospital	3	1%	81	31%	0	0%
Total	442		265		18	

Note: Sample is restricted to independent general-service hospitals present in the AHA data in 1984. Federal and state hospitals and hospitals located in U.S. territories are excluded. The total number of new affiliations in this sample does not equal the change in the number of independent hospitals in Table 1 due to new entry as well as omission from the 1984 survey.

Table 3. Examples of Policy Change

DRG code	Description in 1987 (Description in 1988)	1987 weight	1988 weight	Percent Change in Weight
96	bronchitis and asthma age>69 and/or CC (bronchitis and asthma age>17 with CC)	0.8446	0.9804	16%
97	bronchitis and asthma age 18-69 without CC (bronchitis and asthma age>17 without CC)	0.7091	0.7151	1%
138	cardiac arrhythmia and conduction disorders age>69 and/or CC (cardiac arrhythmia and conduction disorders with CC)	0.8136	0.8535	5%
139	cardiac arrhythmia and conduction disorders age<70 without CC (cardiac arrhythmia and conduction disorders without CC)	0.6514	0.5912	-9%
296	nutritional and misc. metabolic disorders age>69 and/or CC (nutritional and misc. metabolic disorders age>17 with CC)	0.8271	0.9259	12%
297	nutritional and misc. metabolic disorders age 18- 69 without CC (nutritional and misc. metabolic disorders age>17 without CC)	0.6984	0.5791	-17%

Notes: Of the 95 DRG pairs, these three occur most frequently in the 1987 20 percent MEDPAR sample. DRG weights are from the *Federal Register*.

Source: Dafny (2005)

Table 4: New Affiliations in Study Sample

Period	Number of independent hospitals at start of period	FP system	NP system
1985-1987	2616	132	127
1989-1992	2320	76	64
1993-1996	2214	137	203

Notes: Sample restrictions described in text and Appendix Table 1. Only new affiliations with systems of at least 2 other hospitals are reported.

Table 5: Descriptive Statistics, by Time Period

Variable	Source, years available	1985-87	1989-92	1993-96
<i>Key Explanatory Variables</i>				
RTU	MEDPAR, annual	.814 (.353)	6.64 (2.50)	4.98 (2.17)
Residual profit	HCRIS, annual	.527 (7.35)	.798 (7.97)	.572 (7.34)
<i>Hospital Controls</i>				
For-profit	AHA, annual	3.5%	3.8%	4.6%
Government	AHA, annual	34.5%	32.3%	31.0%
Nonprofit	AHA, annual	62.0%	63.9%	64.4%
Teaching	AHA, annual	6.8%	6.5%	5.7%
Number of beds	AHA, annual			
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	AHA, annual	.372 (.108)	.383 (.105)	.419 (.115)
Medicaid share of discharges	AHA, annual	.102 (.071)	.119 (.084)	.164 (.106)
Medicare case-mix index	Medicare Impact Files, annual	1.096 (.119)	1.175 (.153)	1.229 (.200)
Count of hi-tech services	AHA, annual	1.352 (1.698)	1.621 (1.705)	1.927 (1.740)
<i>Market Controls</i>				
MSA Population	AHA, annual			
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	Laurence Baker, annual for 1990+	.099 (.111)	.099 (.110)	.115 (.116)
Zipcode per-capita income	U.S. Census, 2000	19,353 (7580)	19,557 (7785)	19,569 (7565)
Zipcode % black	U.S. Census, 2000	.125 (.190)	.128 (.191)	.126 (.189)
Zipcode % urban	U.S. Census, 2000	.712 (.303)	.724 (.295)	.732 (.286)
N		2616	2320	2214

Notes: Variables available annually are measured as of the year prior to the start of the time period, with the exception of RTU, residual profit, and CMI for 1985-1987, for which 1985 values are reported. Baker's HMO penetration estimates are derived using data from the Group Health Association of America (1990-1994) and Interstudy (1995-96). We use Baker's 1990 estimates for all regressions utilizing data prior to (and including) 1990. For hospitals in zipcodes that do not appear in the 2000 Census files, we use Census data for the corresponding zipcode from a later year; if unavailable, we assign the state-level mean values. Per-capita income squared is also 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.

Table 6: Determinants of New FP System Affiliations, Treatment Period (1989-92)

	(1)	(2)	(3)	(4)
RTU	0.0024*	0.0019**		
	(0.0013)	(0.0010)		
RTU Quintiles				
2			0.0132	0.0110
			(0.0129)	(0.0103)
3			0.0078	0.0096
			(0.0123)	(0.0105)
4			-0.0050	0.0007
			(0.0105)	(0.0088)
5			0.0287**	0.0241**
			(0.0153)	(0.0138)
Residual Profit	-0.0006	-0.0005*		
	(0.0004)	(0.0003)		
Residual Profit Quintiles				
2			-0.0016	0.0012
			(0.0094)	(0.0075)
3			-0.0008	0.0008
			(0.0096)	(0.0074)
4			-0.0077	-0.0045
			(0.0087)	(0.0065)
5			-0.0144	-0.0122*
			(0.0079)	(0.0059)
Region fixed effects	Y	Y	Y	Y
Hospital and Market Controls	N	Y	N	Y
N	2320	2093	2320	2093
Mean(dependent variable)	.0328	.0363	.0328	.0363

Notes: Table reports estimated marginal effects (standard errors) of covariates on the probability of affiliation, evaluated at sample means. The p-values correspond to the hypothesis test of the underlying probit coefficient being equal to zero. (These are the estimates and p-values produced by the “dprobit” command in Stata.) Some controls and associated observations are dropped as they perfectly predict failures; this generates small differences in N across models.

* denotes $p < .10$, ** denotes $p < .05$, *** denotes $p < .01$

Table 7: Determinants of New FP System Affiliations, Pre (1985-87) and Post (1993-96) Periods

Time Period	(1) 1985-87	(2) 1985-87	(3) 1993-96	(4) 1993-96
RTU Quintiles				
2	0.0101 (0.0135)	0.0106 (0.0112)	-0.0022 (0.0131)	-0.0010 (0.0125)
3	-0.0039 (0.0123)	0.0028 (0.0106)	0.0056 (0.0142)	0.0095 (0.0140)
4	-0.0106 (0.0115)	-0.0038 (0.0098)	-0.0035 (0.0134)	0.0029 (0.0136)
5	-0.0130 (0.0113)	-0.0110 (0.0087)	-0.0098 (0.0125)	-0.0034 (0.0128)
Residual Profit Quintiles				
2	-0.0207* (0.0095)	-0.0118 (0.0080)	-0.0110 (0.0112)	-0.0025 (0.0115)
3	-0.0286*** (0.0088)	-0.0186** (0.0073)	-0.0303*** (0.0096)	-0.0232** (0.0095)
4	-0.0298*** (0.0087)	-0.0220*** (0.0068)	-0.0345*** (0.0092)	-0.0276*** (0.0090)
5	-0.0302*** (0.0084)	-0.0255*** (0.0063)	-0.0339*** (0.0089)	-0.0291*** (0.0084)
Region fixed effects	Y	Y	Y	Y
Hospital and Market Controls	N	Y	N	Y
N	2574	2574	2214	2214
Mean(dependent variable)	.0505	.0505	.0619	.0619

Notes: Table reports estimated marginal effects (standard errors) of covariates on the probability of affiliation, evaluated at sample means. The p-values correspond to the hypothesis test of the underlying probit coefficient being equal to zero. (These are the estimates and p-values produced by the “dprobit” command in Stata.) Some controls and associated observations are dropped as they perfectly predict failures; this generates small differences in N across models. For 1985-87, RTU quintiles are calculated using 1988 RTU. For 1993-1996, RTU quintiles are based on 1992 RTU.

* denotes $p < .10$, ** denotes $p < .05$, *** denotes $p < .01$

Table 8: Determinants of New NP System Affiliations, Treatment Period (1989-92)

	(1)	(2)	(3)	(4)
RTU	0.0004 (0.0012)	0.0005 (0.0012)		
RTU Quintiles				
2			0.0009 (0.0105)	0.0012 (0.0096)
3			0.0152 (0.0127)	0.0135 (0.0120)
4			0.0127 (0.0122)	0.0123 (0.0118)
5			0.0055 (0.0112)	0.0064 (0.0110)
Residual Profit	-0.0009*** (0.0004)	-0.0009*** (0.0003)		
Residual Profit Quintiles				
2			-0.0123 (0.0066)	-0.0115* (0.0059)
3			-0.0108 (0.0067)	-0.0101* (0.0060)
4			-0.0090 (0.0068)	-0.0090 (0.0059)
5			-0.0202*** (0.0057)	-0.0181*** (0.0051)
Region fixed effects	Y	Y	Y	Y
Hospital and Market Controls	N	Y	N	Y
N	2234	2146	2234	2146
Mean(dependent variable)	.0286	.0298	.0286	.0298

Notes: Table reports estimated marginal effects (standard errors) of covariates on the probability of affiliation, evaluated at sample means. The p-values correspond to the hypothesis test of the underlying probit coefficient being equal to zero. (These are the estimates and p-values produced by the “dprobit” command in Stata.) Some controls and associated observations are dropped as they perfectly predict failures; this generates small differences in N across models.

* denotes $p < .10$, ** denotes $p < .05$, *** denotes $p < .01$

Table 9: Determinants of NP System Membership, Pre (1985-87) and Post (1993-96) Periods

Time Period	(1) 1985-87	(2) 1985-87	(3) 1993-96	(4) 1993-96
RTU Quintiles				
2	0.0000 (0.0119)	0.0009 (0.0115)	0.0032 (0.0183)	-0.0005 (0.0168)
3	0.0038 (0.0121)	0.0053 (0.0121)	-0.0127 (0.0172)	-0.0164 (0.0156)
4	0.0083 (0.0125)	0.0099 (0.0125)	-0.0155 (0.0171)	-0.0205 (0.0155)
5	0.0006 (0.0116)	0.0015 (0.0114)	-0.0266 (0.0163)	-0.0233 (0.0153)
Residual Profit Quintiles				
2	-0.0013 (0.0101)	-0.0006 (0.0098)	0.0172 (0.0200)	0.0131 (0.0186)
3	-0.0156 (0.0087)	-0.0150 (0.0082)	0.0055 (0.0191)	0.0060 (0.0180)
4	-0.0340*** (0.0071)	-0.0319*** (0.0068)	0.0229 (0.0202)	0.0157 (0.0185)
5	-0.0290*** (0.0073)	-0.0294*** (0.0067)	-0.0350** (0.0162)	-0.0267 (0.0156)
Region fixed effects	Y	Y	Y	Y
Hospital and Market Controls	N	Y	N	Y
N	2574	2487	2214	2214
Mean(dependent variable)	.0470	.0487	.0917	.0917

Notes: Table reports estimated marginal effects (standard errors) of covariates on the probability of affiliation, evaluated at sample means. The p-values correspond to the hypothesis test of the underlying probit coefficient being equal to zero. (These are the estimates and p-values produced by the “dprobit” command in Stata.) Some controls and associated observations are dropped as they perfectly predict failures; this generates small differences in N across models. For 1985-87, RTU quintiles are calculated using 1988 RTU. For 1993-1996, RTU quintiles are based on 1992 RTU.

* denotes $p < .10$, ** denotes $p < .05$, *** denotes $p < .01$

Table 10: Change in Room to Upcode Following System Affiliation

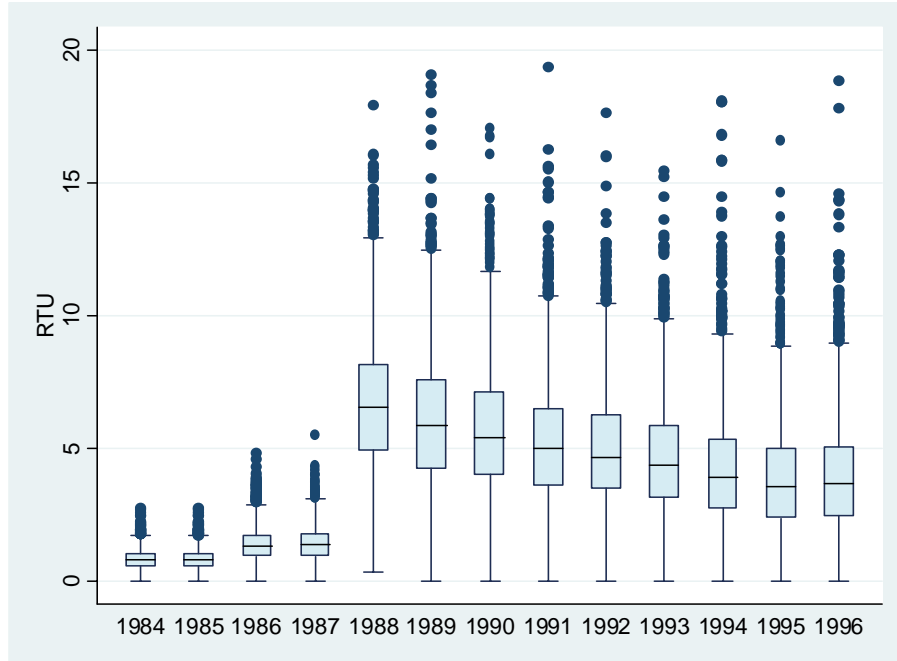
	FP System		NP System	
	(1)	(2)	(3)	(4)
Average Treatment Effect	-0.989**	-0.856**	0.260	0.569
	(0.425)	(0.412)	(0.466)	(0.447)
Number of treatment hospitals	69	75	60	60
Number of matches per treatment hospital	3	5	3	5
Total number of observations	260	372	205	284
Mean of dependent variable	-1.817	-1.884	-1.511	-1.667
Std error of dependent variable	(2.994)	(3.081)	(2.793)	(2.893)

Notes: Dependent variable is the change in RTU over a four-year period spanning the year before affiliation, $t(a)$, to 3 years after, i.e. $RTU_{hjr, t(a)+3} - RTU_{hjr, t(a)-1}$. 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 is smaller than that reported in Table 4 due to missing data for the dependent variable.

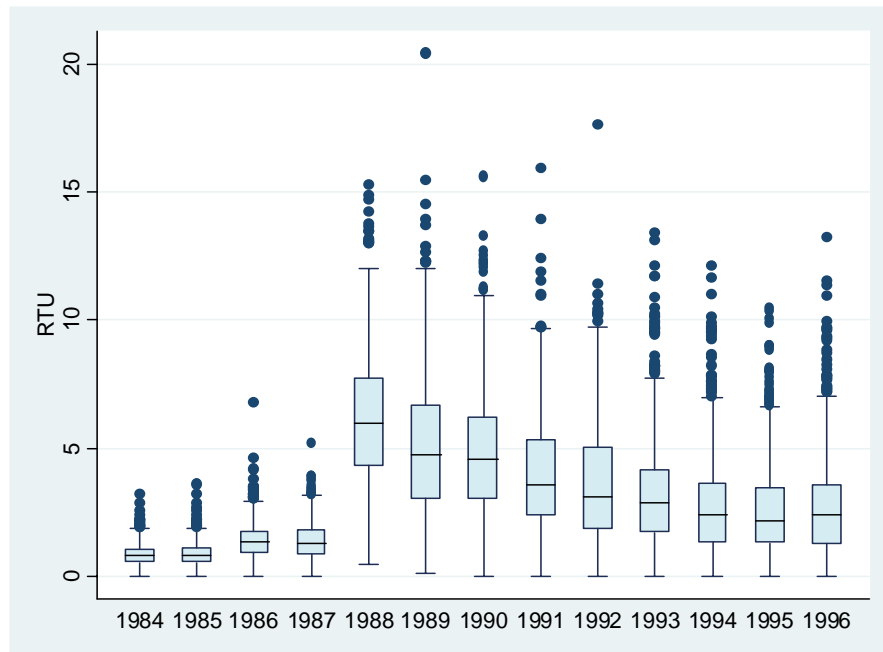
* denotes $p < .10$, ** denotes $p < .05$, *** denotes $p < .01$

Figure 1. Annual Distribution of Room to Upcode, 1984-1996

a. All community hospitals



b. For-profit system members



Notes: Figures pertain to general, non-federal, non-state hospitals in the non-territorial U.S. with 50+ discharge records in the MEDPAR database. Only FP systems with 3+ members are included in Figure 1b.

Appendix Table 1: Sample Restrictions

Time Period	1985-87	1989-1992	1993-96
Hospitals in base year	7110	7037	6732
Number remaining after excluding hospitals with the following characteristics:			
Non-general service	6025	5770	5434
State or federal	5613	5361	5047
Located in U.S. territories	5566	5313	5008
System members in base year	3521	3144	3011
<=50 observations in Medpar	2942	2606	2477
Church-operated	2808	2485	2369
<=30 beds	2674	2367	2219
Missing data	2616	2320	2214

Notes: Data pertains to the year prior to the start of each study period, e.g. the analysis of affiliations between 1985 and 1987 includes hospitals satisfying all of the above criteria in 1984.

Data Appendix

Identifying New System Affiliations

The system identifier in the AHA data files is somewhat noisy. This section describes the problems we identified 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 as 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 system id gap (described above) 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 where 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 are taken as 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 3+ 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 her 2004 article in *Health Services Research*, entitled “Multihospital System Membership and Patient Treatments, Expenditures, and Outcomes.” She too “fills in gaps” when hospitals disappear from and reappear back into the same system. She adds system identification 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.

System Ownership

System ownership type is not included in the AHA data files. We use the following procedure: (1) for systems with more than 10 hospitals, ownership is determined using the AHA guides; (2) for systems with fewer than 10 hospitals, ownership status is determined using a simple majority rule: a system is designated as FP if the number of for-profit hospitals in the system exceeds the number of nonprofit hospitals and the number of government hospitals. Ties are resolved using the AHA guides.