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Patient Admission Patterns and
Acquisitions of "Feeder" Hospitals

by

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Abstract

Large, urban tertiary care hospitals often acquire outlying community hospitals. One possible motivation is to increase referrals. Sophisticated acquirers may even attempt to concentrate additional referrals among more profitable patients. We explore these issues by studying 26 vertical acquisitions in Florida and New York that occurred in the late 1990s, a peak period for such transactions. We compare changes in referrals of patients from target market areas to changes in a matched set of control markets. We find that roughly 30 percent of the vertical acquisitions resulted in a significant increase in referrals to the acquirer. Very few acquisitions were followed by decreases in referrals. When acquisitions did lead to increased referrals, the effect was usually largest for patients with more remunerative insurance and patients undergoing more profitable procedures. However, we find no evidence that hospitals selectively avoided referrals of patients with severe conditions for which costs might exceed reimbursements.

1. Introduction

During the 1990s, hospitals consolidated at an unprecedented pace.[1] Many of these hospital mergers had a distinctly vertical flavor, involving the acquisition of a "plain vanilla" community hospital by a high tech tertiary care hospital. Burns and Pauly (2002) identify several potential goals of such integration, including improving productive efficiency.[2] Burns and Pauly also suggest that many acquiring hospitals viewed their targets as "feeder" hospitals and expected the acquisitions to result in increased referrals.

This paper studies whether vertical integration did in fact generate increased referrals. To our knowledge, the only other study that addresses this issue is Huckman (2006), which finds that vertical hospital integration in New York State led to increased referrals for cardiac surgery. We advance upon Huckman's work in a number of ways. First, we study both Florida and New York. Second, we study each acquisition individually, rather than report an overall trend. This refinement to the empirical strategy allows us to explore the distribution of acquisition effects in greater detail. For example, while Huckman finds that, on average, acquisitions led to increases in referrals (a finding we replicate with our sample of acquisitions), we find that this occurs only in a minority of acquisitions. Additionally, we use a matched target-control framework that generates more reliable estimates of the acquisition effect.

We also explore the interesting possibility that hospitals change referrals patterns selectively. Our motivation for this extension is very simple: not all hospital inpatient admissions are equally profitable. The extent to which hospitals engage in selective referrals is a key issue

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[1] See Bazzoli et al. (2001) and Thorpe et al. (2000).

[2] Analysts have identified many rationales for horizontal hospital consolidations, including market power and economies of scale. For example, see Conner et al. (1998) and Dranove and Shanley (1995).

for a number of ongoing policy debates. For example, as detailed in the next section, private hospitals are often accused of shunning Medicaid and other indigent patients, leaving public hospitals to shoulder the burden. To take another example, allegations that physician-owners of specialty hospitals opportunistically distort their referral decisions led Congress to insert a provision banning the construction of new physician-owned specialty hospitals into the Medicare Modernization Act of 2003. We examine whether hospitals engage in three distinct forms of selective referrals, explained in detail in Section 2.2: insurer-based, procedure-based, and severity-based selection. We find evidence of the first two forms of selection, but reject the hypothesis that acquirers engage in severity-based selective referrals.

2. The Hospitalization Decision

2.1 Acquiring Referrals

Patients cannot admit themselves to a hospital; only licensed physicians with admitting privileges can do so. This would be a distinction without a difference if physicians acted as perfect agents for their patients. In practice, physicians can strongly influence patients' admissions decisions.[3] As is typical in principal-agent relationships, such as the patient-physician relationship, patients lack the necessary information to discern whether their physician's referrals are driven solely by the interests of the patient, or by other factors.[4] As a result, hospitals seeking to increase referrals might conclude that the "way to patients' hearts" is through their physicians. For example, in the 1970s and 1980s hospitals tried to induce physician referrals by purchasing

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[3] See, for example, the surveys of patients by Sarel (2005) and Smithson (2003).

[4] Over 40 years ago, Arrow (1963) observed that, "…because medical knowledge is so complicated, the information possessed by the physician as to the consequences and possibilities of treatment is necessarily very much greater than that of the patient, or at least so it is believed by both parties. Further, both parties are aware of this information, and their relation is colored by this knowledge."

costly medical equipment and extensive staffing of allied medical personnel, a practice dubbed "the medical arms race."[5] The emergence of managed care and the concomitant practices of utilization review and selective contracting reduced the effectiveness of this tactic.[6]

Beginning in the early 1990s, a new strategy gained prominence as large tertiary care hospitals began acquiring physician practices and community hospitals, anticipating that they would "acquire" their patients as well. They were forced to integrate, rather than contract, by ethical and legal constraints. In particular, the 1972 *Anti-Kickback Law* formalized the medical profession's longstanding ethical ban on payment for referrals; additional restrictions were later imposed under the 1989 and 1995 *Stark I* and *Stark II* laws.[7]

The *Anti-Kickback Law* subjects any physician who "knowingly and willfully solicits or receives any remuneration [for referring Medicare or Medicaid patients]" to civil and criminal charges. While seemingly strict, prosecutions under this law were rare (Hyman 2001). Morrison (2000) attributes this rarity to the difficulty of establishing intent and the ambiguity of the phrase "knowingly and willfully." *Stark I* banned referrals of Medicare patients for clinical laboratory services if the referring physician has a financial relationship with the laboratory, regardless of the intent of the parties. *Stark II* expanded the ban on physician-provider payments to include all

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[5] Robinson and Luft (1985). Costly and high-tech medical equipment is a consumption good for many doctors and thus, in the medical arms race model, serves as in-kind compensation for referrals. Similarly, physicians prefer high staffing levels to low ones.

[6] Zwanziger and Melnick (1988).

[7] See *Anti-Kickback Law* (42 U.S.C. § 1320a-7b(b)); *Stark I/II* (42 U.S.C. § 1395nn; Social Security Act § 1877 and §1903(s)). In 1992, the Health Care Financing Administration, since renamed the Centers for Medicare and Medicaid Services (CMS), issued a set of physician referral guidelines and outlined a number of safe harbors for permitted referral activities (42 C.F.R. § 411.350).

hospital services reimbursed under Medicare or Medicaid, also without regard to intent. The two states we study, New York and Florida, have additional laws governing compensated referrals.[8]

Certain forms of payment are permitted under all three of these laws. For example, the *Anti-Kickback Law* allows "payments pursuant to employment relationships" as well as payments between tax-exempt hospitals providing shared services if they form "cooperative hospital service organizations."[9] Similarly, *Stark II* allows physicians to refer patients to hospitals where they have minimal ownership interests. Additionally, while Stark laws prohibit payments from an employer to a physician that are contingent upon the volume or value of referrals, physicians are allowed receive productivity bonuses (Morrison 2000). Overall, ownership of a physician group gives a hospital more latitude, though still limited, to encourage physician referrals from that group. To be entirely safe, physicians whose practices are acquired should be able to demonstrate that changes in referrals serve patients' best interests – for example, by demonstrating that the acquirer has improved quality.

There are a number of ways in which acquiring hospitals might expect the acquisition of feeder hospitals to increase referrals, none of which necessarily run afoul of the law. The acquirer may grant admitting privileges to the medical staff of the target as well as acquire any physician practices owned by the target. Specialists at the acquirer and the feeder medical staffs may begin sharing information, for example through meetings or unified clinical information systems. The acquirer might establish a stronger presence in the feeder's community, increasing demand

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[8] Florida applies provisions similar to the *Stark* restrictions to all patients, regardless of insurer (*Florida Patient Self-Referral Act of 1992*, Florida Statutes, 456.654); New York does allow compensated referrals for inpatient services where not prohibited by Stark, but requires the physician to disclose any financial interests in the referred provider (NY Pub. Health Law, Title II-D, § 238.)

[9] Hyman (2001) and Morrison (2000) discuss employment relationships; Hubbel et al. (2006) and Morrison (2000) discuss the relationship between referral regulations and cooperative ventures.

directly through patients. In any event, Burns and Pauly's (2002) survey of hospital executives indicates that acquirers clearly expected a payoff in terms of increasing admissions. As detailed below, an acquirer might even be able to "cherry-pick" the most profitable patients from the target hospital's market or "dump" the least profitable, further increasing the profitability of the acquisition.

Vertical integration can also generate increased referrals to the acquirer if it is accompanied by quality enhancements. Unless such enhancements are specific to the acquirer/target pair, such as a unified clinical information system, we expect quality improvements to generate increased referrals from other market areas as well. We take care in our empirical work to distinguish between increased volume resulting from a general increase in quality at the acquiring hospital and increased volume specific to the target hospital's market area.

2.2 Referrals and Profits

Although revenues per admission vary by payer (e.g., Medicaid versus private insurance) and disease, hospitals expect to at least cover incremental costs for most admissions. A recent study by Friedman et al. (2004) indicates that for the average hospital in several states studied, total inpatient revenue exceeds total cost. Friedman et al. also find that the revenue to total cost ratio varies by payer but is never lower than 75.4% (Medicaid in California, the stingiest payer in their study). Accordingly, if fixed costs constitute more than 25% of total costs, as strongly suggested by Friedman and Pauly (1981), as well as by cursory examination of hospital expense

data, then it stands to reason that even the least remunerative insured patients generate positive net marginal revenues on average.[10]

This does not imply that all admissions are equally profitable. Friedman et al. (2004) finds that Medicaid is a stingy payer relative to Medicare and traditional indemnity insurers. Profits also vary by type of treatment. There is a general consensus that cardiac treatment is more profitable than most other treatments. For example, Huckman (2006) estimates that average margins are $3900 for Coronary Artery Bypass Graft (CABG) surgery and $2700 for Percutaneous Transluminal Coronary Angioplasty (PTCA); more importantly, he estimates that marginal profits are $6200 for CABG and $4900 for PTCA. The implied double digit profit margins for these procedures are well above hospitals' overall margins.

Two patients who receive the same treatment and have the same insurer may not be equally profitable. Medicare and some private insurers pay hospitals a fixed fee per admission based on the diagnosis related group, or DRG. The Center for Medicare and Medicaid Services (CMS) attempts to set DRG payments near the mean cost of treating each diagnosis, but cost can still vary significantly within a diagnosis. For example, Dranove (1987) observes that the coefficient of variation of treatment costs exceeds 1 for many DRGs. Because revenue is fixed and costs vary, the profitability of patients in a given DRG varies inversely with expected treatment costs.

This discussion suggests that if it is costly for an acquirer to expand admissions, it might not seek to do so across-the-board. Acquirers might instead focus their efforts on patients with good insurance, patients with cardiac disease and other relatively profitable conditions, and

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[10] There are no definitive studies of the incremental profitability of admissions. This somewhat dated study by Friedman and Pauly pegs long run variable cost at just half of total cost. Analysis of (unaudited) accounting data suggests that allocated overhead may amount to as much as half of total costs.

relatively healthy patients within each diagnostic class. Respectively, we label these three mechanisms insurance-based, procedure-based, and severity-based selective referrals. Hospitals may use several tactics to implement these strategies, including judicious granting of admission privileges, strategic location of outpatient facilities, service enhancements (e.g., using the latest coronary stents), advertising (e.g., promoting a cardiac care "center of excellence"), cajoling admitting physicians, or through outright refusal of transfers based on expected profitability.

Several prior studies of admission patterns suggest that hospitals pursue such strategies. Duggan (2002) finds that the introduction of a state program to increase payments to hospitals that treat medically indigent resulted in a shift of Medicaid patients from government-owned to private hospitals. Newhouse (1989) finds that patients in less profitable DRGs are more likely to be admitted to publicly-owned hospitals. While these studies present strong evidence of payer-based selective referrals, evidence of severity-based selection is mixed. Rosko and Carpenter (1994) find that intra-DRG severity of illness is positively related to expenditures and is inversely related to hospital profits, indicating the potential for severity-based referrals to increase profits. Even so, Newhouse (1989) finds that high-severity patients are no more likely to be treated at public hospitals than private hospitals, suggesting that private hospitals do not shun high-severity patients. However, a more recent study by Meltzer et al. (2002) finds that after Medicare introduced the Prospective Payment System (PPS), hospitals selectively reduced spending on the most severely ill and thus the most costly patients within the same DRGs. They conclude that hospitals do attempt to discourage admissions of unprofitable patients by lowering the quality and treatment intensity for such patients. They also find the same trend for non-Medicare patients, suggesting that hospitals changed their practice style for the entire set of patients.

A common thread throughout the papers cited in this section is evidence that physicians, or at least some physicians, can and do respond to economic incentives in making their referral and admission decisions.[11] Indeed, this proposition is the reason for the existence of the laws described in the previous section. The underlying mechanisms that create such incentives are largely unexplored in the current literature, treated instead as a black box. Exploring the contents of that box is beyond the scope of this paper. Instead, we follow the literature and take the existence of such mechanisms as given and explore whether, and how, they are manifested in the context of acquisitions of feeder hospitals.

3. Estimation Method

3.1 Identification of Hospital Acquisition

We study consolidations in which one of the hospitals may be considered a tertiary care hospital and the other is not. For New York, we use the list of hospital acquisitions provided to us by Robert Huckman, limiting our analysis in New York to acquisitions that occurred from 1996 to 1999, for a total of 21 hospital pairs.[12] We also examine six acquisitions in Florida, which we identify using from data obtained from Irvin Levin Associates.[13]

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[11] Yet another example is the ongoing debate over *economic credentialing* – hospitals denying admitting privileges to physicians based on economic criteria, such as an ownership stake in a rival ambulatory surgery center, rather than clinical criteria. See, e.g., Nagele (2003).

[12] We study these states and years primarily because of data availability. This was a also peak period for vertical acquisitions: 23 out of 35 mergers studied by Huckman (2006) occurred in this window.

[13] We add Florida primarily because of data availability. In Florida a large number of community care hospitals were acquired by "vertical health systems" during the time period, but the majority of them were parts of large but disjointed health systems, such as Columbia/HCA. We view these as system expansions rather than potentially vertical mergers. After excluding such system expansions, we are left with six vertical mergers in Florida.

Following Huckman (2006), we identify transactions in which one hospital provided open heart surgery and the other did not.[14] We define the former as the acquirers and the latter as the targets and study admission patterns for CABG and PTCA procedures. Based on American Hospital Association data, we observe that the acquirers invariably offer a wider range of specialized services, such as radiation therapy and transplants, than their targets (see Appendix A). Thus, we also study admission patterns for a broader class of tertiary care services that we define below. This is an important extension because, as Huckman observes, cardiac services are generally believed to be more profitable than most other hospital services and may therefore exhibit different post-acquisition referral effects.

3.2 Identification of Referral Effects

Our goal is to determine whether patients who reside in the target hospital's market area are more likely to obtain cardiac and other tertiary care services at the acquiring hospital after the acquisition. To do so, we need to control for the possibility that the acquiring hospital becomes more attractive to all patients, not just those in the target market (see Figure 1). We do this by identifying, for each target hospital market, a set of "control" markets. The control markets have two important features: (a) prior to the acquisition, the acquirer's share of patients in the control market was comparable to its share in the target market, and (b) the patients in the control market would not normally consider visiting the target hospital (and would therefore be unaffected by the acquisition, except to the extent that it was associated with overall improved quality at the

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[14] In a few cases, the acquiring organization included several tertiary care hospitals. In such cases, we attempted to identify a single "flagship" acquiring hospital based on AHA data and the system's web page. When no clear flagship hospital existed, we treat the system's tertiary hospital closest to the target as the acquirer. In Florida, we use the condition the acquirer performed at least 50 surgeries and the target no more than 20 over the sample period.

acquiring hospital.) With suitable control markets in hand, we can determine whether the acquirer's share increased more within the target market than in the control markets.

We used a flexible approach to define target and control markets, letting common sense be our guide. As illustrated in Figure 2, we began by considering the set of all zip codes within a fixed radius of the acquiring hospital. The size of the radius varied inversely with the size of the MSA in which the target was located. Thus, for targets in the largest MSAs, we only included zip codes within a 5 mile radius; for the smallest MSAs, we used a 25 mile radius (all the acquisitions we studied were in MSAs). We then sought to identify a set of candidate control zip codes that are (1) closer to the acquirer than they were to the target, and (2) not located in between the acquirer and the target. Thus patients in our ideal control markets had the potential to visit the acquirer, but were unlikely to select the target hospital.

A number of complicating factors force us to manually tailor the target and control zip codes for some acquisitions. In several cases, a single acquirer purchased several hospitals in the same year. In such cases, we choose the control group so that none of the control zip codes were near any of the target hospitals, because our key identifying assumption is that the changes in shares in the control markets reveal the changes in market share that the acquiring hospital would experience in the absence of an acquisition. More mundanely, we also exclude zip codes in cases where intervening bodies of water and the locations of bridges imply that they are not properly part of either the target or control markets, despite short straight line distances.

In four cases, the target and the acquirer are very close neighbors.[15] We question whether it is appropriate to examine the referral issue in this context, as the vertical issue of referrals is

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[15] In Florida, there were two purchases of targets in the same zip code as the acquirer: Halifax's purchase of Atlantic-Daytona and Shands' purchase of Methodist Medical Center. In New York, New York Hospital purchased a

intertwined with horizontal issues such as market power and clinical integration. Pragmatically, the set of zip codes in this case that are close to the acquirer but far from the target is nearly empty. Primarily to compare our results with the results in Huckman (2006), we do our best to identify a reasonable set of target and candidate control markets for these cases, though we are skeptical of the results obtained from these particular acquisitions.

While this procedure is necessarily *ad hoc* for some of the mergers, we believe that, with the possible exception of a few acquisitions involving a proximate target, we constructed reasonable target and control areas for each acquisition. A complete set of maps identifying the target and candidate control zip codes for each acquisition is available upon request.

After identifying a set of candidate controls, we winnow the set of candidate control zip codes into the set of actual control zip codes by matching on pre-acquisition market shares. This step is crucial because of the underlying nonlinearity of the logit demand specification we use in the empirical model. This nonlinearity can generate misleading results in difference-in-differences analyses.[16] To eliminate this concern, we select control markets in which the acquirer's share is "close" to its share in the target market. To implement this, we calculate each acquirer's zip code level market share in the pre-acquisition period, which we define as beginning at the start of our data and continuing to 2 years prior to the acquisition year.[17] To be

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neighboring hospital, Flushing Medical Center, and Buffalo General's purchased Buffalo Columbus Hospital, located 1.2 miles away.

[16] In particular, when a predictor variable in a logit regression changes value, the predicted change in the dependent variable depends on the initial market share. For example, suppose that the initial market shares of the acquiring hospital in the control and target markets are 5 percent and 40 percent respectively. If the share in the control market increases to 10 percent, then the logit structure would dictate that the predicted share in the target market would be 65 percent. If the share increased to "only" 60 percent, the regression would report a negative acquisition effect, a result driven entirely by functional form. Note that this problem is potentially endemic in Huckman (2006).

[17] The first years are 1994 and 1995 in Florida and New York, respectively. If the acquirer began offering open-heart surgery after the first year, we define the year that they started offering the service as the first year for the CABG/PTCA estimation.

considered close, the market share in the control zip code must be within a certain range of the

share in the target zip code, with the range depending on the initial share in the target market (see

Figure 3). We apply a more refined matching criterion to selecting control markets for the

tertiary DRG sample because that sample contains nearly ten times as many observations.[18]

3.3 Treatments and Diagnoses Studied

We conduct the analysis on two sets of procedures: highly profitable CABG/PTCA

procedures, and a broader set of "tertiary" DRGs, which we defined as DRGs that (1) were

notably more likely to be performed at large hospitals than small hospitals,[19] and (2) had a

Medicare case-weight of at least .50.[20] Appendix A lists the 36 DRGs we classify as tertiary; note

that this set includes both CABG and PTCA.

3.4 Selective Referral Hypotheses

We test the three referral hypotheses by assessing whether changes in referral patterns are

the same for all affected patients. Specifically, we examine whether referral patterns vary

systematically by treatment (i.e., cardiac versus broader tertiary diagnoses), payer type, and

expected treatment costs.

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[18] See Appendix C for a comparison of the acquisition effects estimated using only the matched control zip codes to the acquisition effects estimated using *all* candidate control zip codes (with both models estimated using a linear probability model). That both models yield similar results is evidence that the results are not driven by sample selection bias in our control zip code selection algorithm.

[19] We classified hospitals with over 500 beds as large and hospitals with under 100 beds as small. We then identified DRGs such that (i) the percentage of patients in that DRG admitted to small hospitals was below 5% and the percentage admitted to large hospitals exceeded 10%, or (ii) the percentage admitted to small hospitals was both below 10% and less than half the percentage admitted to large hospitals. To avoid potential sample selection biases, we used 1997 Arizona data to identify our set of tertiary DRGs. Finally, we omitted DRGs with fewer than 500 observations statewide.

[20] The Medicare caseweight reflects the average cost of treating a patient in a given DRG. The patient-weighted average caseweight across all DRGs is about 1.2.

We do not have an ideal metric for expected treatment costs. We consider two proxies: list charges and the number of diagnoses (diagnoses are only reported in New York). List charges are derived from the services provided to patients and each hospital's "charge master," a comprehensive catalog of a hospital's list prices for every individual service. Accordingly, Medicare patients within a given DRG who consume a great deal of resources will have high list charges but the same reimbursement as other patients in the same DRG, making them less profitable.[21] The same applies to many HMO patients. The number of reported diagnoses is also an imperfect measure of costs; in general, however, patients in a given DRG with more reported diagnoses have more complications and require more intensive care (Muñoz et al. 1988).

4. Estimation

4.1 Acquirer Share Effects

For each acquisition, we estimate logit models of hospital choice separately for CABG/PTCA patients and for tertiary patients. We use discharge data from 1995 to 2000 for the state of New York and 1994, 1996, 1998, 2000, and 2002 for the state of Florida. The dependent variable Y equals 1 if the patient chose the acquirer and 0 otherwise. The logit regression model, which we estimate using all patients in the target and control markets, is:

$$\Pr(Y_i = 1) = \frac{\exp\left(\boldsymbol{b}_0 + \boldsymbol{b}_1 Year_t + \boldsymbol{b}_2 X_i + \boldsymbol{b}_{D1} D_i + \boldsymbol{b}_{D2} D_i^2 + \boldsymbol{b}_E E_i + \boldsymbol{b}_T T_i + \boldsymbol{b}_{TA} TA_i\right)}{1 + \exp\left(\boldsymbol{b}_0 + \boldsymbol{b}_1 Year_t + \boldsymbol{b}_2 X_i + \boldsymbol{b}_{D1} D_i + \boldsymbol{b}_{D2} D_i^2 + \boldsymbol{b}_E E_i + \boldsymbol{b}_T T_i + \boldsymbol{b}_{TA} TA_i\right)}. \quad (1)$$

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[21] Medicare, like most private insurers that use case rates, has outlier provisions under which particularly expensive cases are reviewed and payments may be increased. For Medicare, such outlier payments accounted for between 5 and 7.5 percent of total Medicare inpatient spending and well under 5 percent of discharges in our sample (Medicare Payment Advisory Commission, 2002).

Year_t is a vector of year fixed effects, $\boldsymbol{X}_i$ is a vector of demographic and clinical characteristics of patient i, $\boldsymbol{D}_i$ is the driving time from i's zip code to the acquirer, T_i is a dummy variable indicating whether i lives in the target market, and TA_i is an indicator variable that equals 1 if the patient belongs to the target group and the time is after the acquisition. If the coefficient on the last explanatory variable, $\boldsymbol{b}_{TA}$, is positive and statistically different from zero, then the acquisition increased referrals.

We estimate (1) separately for each acquisition. We control for the patient's age, payer type, the type of cardiac treatment or the major disease category (for cardiac services and tertiary services regressions respectively), and whether the patient had an acute myocardial infarction (AMI, for cardiac services regression only). We also include three indicator variables, E_i, that measure the following events: patient i's zip code was affected by the entry of a new inpatient provider of CABG/PTCA services, i's zip code was affected by a hospital exiting from tertiary care; or i's zip code was included in multiple target markets. Given this structure, if an acquirer's share increases post-acquisition by the same amount in both the target and control markets, then the corresponding year-effects will be positive while β_{TA} will be zero.[22] Conversely, if the increased share is greater in the area surrounding the target hospital, then β_{TA} will be positive and we attribute the increase to the acquisition.

Endogeneity can be a concern with approaches such as this one. For example, acquirers could purchase community hospitals in those areas with favorable demographic and clinical trends that are not captured in our data. While we cannot definitively rule out this possibility, two

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[22] Any change in referrals resulting from a change in quality at the acquiring hospital should be captured by changes in referrals from the control population. Huckman (2006) pools his data, with acquisitions occurring at different points in time, and thereby is unable to control for each hospital's own admissions trend.

factors lessen our concern. First, we focus on shares of patients rather than absolute numbers. Unobserved trends that increase the propensity of residents in the target market to undergo CABG/PTCA or tertiary procedures would increase admissions to all tertiary hospitals drawing from that high growth area, not just the acquirer. Second, we do control for several demographic and clinical characteristics of the target and control populations.

We explored several options for selecting the time period that defines *TA*. Hospital consolidations are usually consummated within months of announcement, but some take longer. It is conceivable that admission patterns could change prior to consolidation if, for example the acquirer had already begun courting physicians. Accordingly, we tried three different model specifications. In the first specification, *TA* = 1 for patients in the target market from the year of the acquisition announcement through all subsequent periods. In the second specification, *TA* = 1 from one year before the acquisition through all subsequent periods. In the third specification, which we focus on in this paper, we set *TA* = 1 in the years following the announcement year and also include a second interaction for the "between period" consisting of the prior year and actual year of the acquisition.[23] Our results are broadly consistent across all specifications.

4.2 Selective Referral Effects and Patient Severity

To identify selective referral effects based on patient severity, we compare the distribution of list charges of Medicare and HMO patients who reside in the target market and are admitted to the acquiring hospital, to Medicare and HMO patients admitted to the acquirer

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[23] Thus, our reported TA coefficients compare the referral probabilities from a time at least one year before the merger to the post-merger period rather than comparing the post-merger period to the entire pre-merger period, which likely includes some transitory effects caused by the merger itself.

from the control markets, before and after the acquisition. We use the same approach to study the effect of the acquisition on the number of diagnosis of Medicare and HMO patients admitted from the target market. both before and after the acquisition. For both diagnoses and charges, we are again interested in the coefficient on TA_i, the indicator for target market patients in the post-acquisition period. We also interact TA_i with an HMO dummy to allow the effects to differ by payer type.

We estimate quantile regressions (see Appendix B) for list charges in order to focus on the patients who are most readily identifiable as unprofitable (the upper end of the list charge distribution) or profitable (the lower end of the charges distribution). Because the number of diagnoses is a count variable, we are unable to estimate quantile regressions, so we instead estimate ordered logit models.[24]

5. Data

For Florida, we use biannual discharge data from the Florida Agency for Health Care Administration (AHCA). For New York, we use annual discharge data from the Health Care Utilization Project (HCUP). Both data sets contain detailed clinical and demographic information for every hospital discharge. Clinical variables include the patient's DRG, secondary diagnoses, and additional procedures. The non-clinical variables we use are age, payer type, and zip code; the latter allows us to identify patients in the target and control markets.

Table 1 contains hospital summary statistics.[25] Whether measured by beds or inpatient days, the acquiring hospitals are over three times larger than targets in New York, and over twice

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[24] We also estimated Ordered Probit models and found similar results (available upon request).

[25] The number of targets exceeds the number of acquirers because some acquirers purchased more than one target.

as large in Florida. Nearly all of the acquirers offer open heart surgery, while only one target in each state did so.[26] Similarly, none of the New York targets and only one of the Florida targets were teaching hospitals, whereas 25% of acquirers in New York and 70% in Florida were teaching hospitals. In both states the targets served a higher proportion of Medicare patients than did the acquirers.

Table 2 contains patient summary statistics. The cardiac patients are significantly older than the tertiary patients. The CABG/PTCA group is also disproportionately white, and, not surprisingly given their average age, contains relatively few Medicaid patients. Within each diagnosis group, the control and target populations are quite similar on average.[27]

6. Results

6.1 Acquirer Share Effects

Before running regressions, we examined whether the average acquisition led to a larger share increase in the target market than in the control markets. Table 3 clearly shows that it did not. In fact, the change in the average acquirer's market share in the target market is slightly below the corresponding change in the control markets, though the difference is not significant.[28]

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[26] This seems like a discrepancy, as all acquirers should, by definition, offer open heart surgery. A hospital can perform a moderate number of CABG/PTCA procedures without the AHA categorizing it as offering open heart surgery. For instance, Crouse Hospital in Syracuse, NY is not classified as performing open heart surgery, but did perform 142 CABGs and PTCAs from 1995-2000. Leesburg Regional Hospital, a Florida target, began offering open heart surgery only after being acquired.

[27] The figures for the control and target groups in Table 2 are averages across all the acquisitions we study. Thus, any single acquisition would likely exhibit somewhat larger variation across the target and control groups.

[28] We also estimated the specifications in Huckman (2006) using our data and replicated his findings that acquisitions do lead, on average, to increases in referrals. This suggests that the difference between our findings is not due to the different time periods and hospitals studied.

This is true for both the CABG/PTCA and the tertiary samples, and remains true when we control for year effects, state effects, or both.

While illustrative, the raw difference-in-difference estimates do not resolve the question of whether acquisitions increase referrals. First, while the average effect of an acquisition appears to be zero, examination of each individual acquisition reveals that a number of them did in fact lead to notable increases in the acquirer's market share in the target market area (Figure 1 contains one example). Second, for the simple estimator to yield an accurate estimate of the marginal impact of the acquisition, the changes in the acquirer's market share in both the target and control markets must, absent the acquisition, be identical in expectation. This condition is unlikely to be met in the data, so a regression-adjusted estimator, as described in equation (1), is appropriate.

Tables 4 and 5 present the results of our Logit regressions for CABG/PTCA patients and tertiary patients, respectively. We did not estimate regressions for a number of the acquisitions. Most of the unestimated acquisitions were dropped because the acquirer's share was very small, below 5 percent, in both the pre- and post-periods; this primarily occurred when acquirer and target were very far apart. These are situations where very few patients in the target market *ever* choose the acquirer, suggesting these acquisitions were likely motivated by considerations other than referrals. We also dropped one case in the CABG/PTCA model in which the acquirer's share was over 95% in both the pre- and post-period. In the remaining cases, unique geography or the presence of other hospitals around the acquirer prevented us from identifying a control market with sufficient observations. Thus, while we began by considering 26 acquisitions, we only estimated the CABG/PTCA model for 13 acquisitions and the tertiary model for 15. These are

the cases for which it is plausible that the acquisition was motivated by a desire to increase referrals and it was possible to perform a reliable analysis of whether this occurred.

Table 4 shows that b_{TA} is significant and positive in five of the thirteen CABG/PTCA models estimated. The column titled 'Marginal Effect' shows the corresponding increase in the probability of a target area resident choosing the acquiring hospital attributable to the acquisition.[29] For example, the acquisition of Amsterdam Memorial by Ellis Hospital increased Ellis' share of CABG and PTCA patients in the area around Amsterdam Memorial by 40 percent, while North Shore Hospital nearly doubled its share in the area around Southside Hospital. Each of these increases represents over 100 additional CABG and PTCA patients annually. Based on the marginal profit numbers cited in Section III, an additional 100 such patients increases hospital profits by roughly $500,000. Across all hospitals that saw a significant effect (all of which are positive), the average increase in market share in the target area was 10 percentage points (7 points if the average is patient-weighted).

Table 5 shows that 10 of the 15 estimated acquisitions had a significant effect on the acquirer's share of tertiary patients in the target market, and 7 of those 10 had a positive effect. (The greater number of significant results in these models largely reflects the larger sample sizes.) Two of the acquisitions with negative effects in this case also had negative, but insignificant effects in the CABG/PTCA sample.[30] As posited under the procedure-based

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[29] This is computed as $E(Y_{i,t} \mid X_{i,t}$, Market=T, t=Post, TA=1)- $E(Y_i \mid X_{i,t}$, Market=T, t=Pre, TA=0). Because we include patient demographics in the Logit model, the value of this expectation depends on the patient characteristics we use to compute it. We use a 65 year old Medicare patient in a zip code not affected by any of the events in E. Note that the marginal effects are equivalent to point increases in expected market share.

[30] These are the acquisition of South Seminole Hospital by Orlando Regional and the Rochester, NY acquisition of Highland Hospital by Strong Memorial. We are not sure why these hospitals lost share in their target markets; it is possible that a rival hospital situated closer to the target than to the control increased its quality, or the acquisition may have been poorly executed.

selective referral hypothesis, the effects for tertiary DRGs, which generally have lower margins, are smaller in magnitude than in the higher margin CABG/PTCA sample. Acquirers whose market share did increase in the target market saw their market share increase by an average of 4.2 points.

A related question is whether the additional admissions constitute an aggregate increase in market share or simply a reallocation of patients from the target to the acquirer. By definition, the referral effects we find for CABG and PTCA represent new business, because we are studying the acquisition of community hospitals that do not offer CABG/PTCA by tertiary hospitals that do. In the broader context of tertiary DRGs, the post-acquisition changes in the combined share of the acquirer and target within the target market are somewhat smaller than the corresponding increase for just the acquirer, but still positive. Thus, while there is some business-shifting, there is still a net increase in volume. For example, the average increase in tertiary market share (in the target market) for both the acquirer and target is 0.33% while the corresponding figure for the acquirer alone is 0.89%.

6.2 Selective Referral Effects

As previously discussed, sophisticated acquirers may seek to increase referrals of patients in proportion to the generosity of their insurers, the profitability of the treatment, and the severity of the patients. Tables 6 and 7 present the marginal effects of acquisition separately for each of the four payer categories used in the estimation: FFS/PPO, Medicare, HMO, and Medicaid/ Indigent. With two exceptions, the acquisitions that have significant effects for at least one payer class also have significant overall referral effects.

Table 8 summarizes these findings, along with the earlier results. The majority of acquisitions led to no significant change in referrals from the target market. However, among those cases in which there was a significant change, the effect was more often positive than negative. The average estimates of b_{TA} across all acquisitions are 0.2320 for CABG/PTCA and -0.0076 for tertiary patients. If we assume that each market is an observation from a common process, we cannot reject the null that the average effect on tertiary referrals is zero (t = -.29). However, we do reject the null that the average effect on CABG/PTCA referrals is zero (t = 3.34).

Turning to selective referral effects, we observe that there are many positive significant referral effects for Medicare patients and few negative effects. In contrast, the few positive effects for Medicaid are largely offset by negative effects. These findings are consistent with selective referrals by payer. On the other hand, there is no apparent difference in the number of positive versus negative referral effects for relatively profitable FFS/PPO patients as compared to relatively less profitable HMO patients, though the magnitudes of positive effects are larger for FFS/PPO patients. Turning to treatment types, we find that 8 out of 9 significant referral effects for CABG/PTCA are positive, compared with 7 of 13 for tertiary (excluding CABG/PTCA). On balance, these patterns are consistent with selective referrals by profitability.

Tables 9 and 10 show the average effect of each merger on the log of list charges, as well as the effects on the .10, .25, .50, .75, and .90 deciles of list charges for CABG/PTCA and tertiary patients, respectively. If acquirers screen based on severity, then we expect the post-acquisition distribution of charges at the acquirer (for patients from the target area) to have more mass at the low end and less at the high end. Note that we are maintaining our difference-in-difference approach in this specification, so we are comparing the post-acquisition distribution of

charges for admissions from the target area to the distribution of admissions from the control area. This also controls for any changes in the acquirer's prices following the acquisition.

None of the results for CABG/PTCA patients with HMO insurance are significant, indicating an absence of severity-based selective referral patterns for these patients. For Medicare patients, many of the effects are significant, but varied. Overall, they are inconsistent with the selective referral hypothesis. While two acquisitions saw, as expected, a significant decrease in the cutoff for the .10 decile of log charges, six entailed increases, meaning that referrals of the least severely ill patients *decreased* (relative to referrals of such patients in the control markets).[31] The results for the most severe Medicare CABG/PTCA patients also contradict the hypothesis: five acquirers significantly increased admissions of severely ill patients, and none decreased such admissions.

In the broader category of tertiary DRGs, shown in Table 10, the picture is similar. None of the HMO effects are significant. If anything, we find fairly strong evidence of decreased, not increased, admissions of lower list charges patients. We also find five of six acquisitions with significant effects lead to increases in the number of admissions of Medicare patients with very high list charges. Based on this evidence, we cannot conclude that the acquirers are screening Medicare tertiary patients based on their severity.

Turning to our second measure of severity, the number of diagnoses (Table 11), we again find evidence that contradicts the hypothesis of selective referrals based on severity. As was the case with list charges, none of the acquisitions had a significant effect on the number of

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[31] Note that a *negative* coefficient for the .10 or .25 quantile indicates *increased* admissions of low-severity patients (because the cut-off, X, such that 10% or 25% of patients have list charges below X shifts to the left post-acquisition.) Conversely, for quantiles above the median, a positive coefficient indicates a rightward shift in the corresponding cutoff, indicating more admissions of high severity patients.

diagnoses of HMO patients, whether CABG/PTCA or tertiary patients, referred from the target market. Only one acquisition was followed by a significant decrease in the number of diagnoses of referred Medicare CABG/PTCA patients (relative to patients admitted from the control area). Three acquisitions had significant increases. Otherwise, the results are insignificant.

For Medicare patients within the broader set of tertiary DRGs, the effects are significant for about half of the acquisitions, but in six of those nine instances, the effect on the number of diagnoses of referred patients is positive rather than negative. Thus, both our examination of list charges and our examination of the number of diagnoses for patients referred from the target area fail to support the hypothesis of severity-based selective referrals. If anything, some acquirers may have increased admissions of more severely ill patients from the target area.

7. Conclusions

Hospital managers usually cite two factors when explaining their motivation for purchasing an outlying community hospital: improving quality at the target and increasing referrals to the acquirer. In this paper, we study the second motivation.[32] Our results indicate that only a minority of acquisitions lead to increases in referrals from the target market, relative to trend.[33] This finding is consistent with the broader strategy literature on mergers and acquisitions, which indicates that while some firms consistently succeed at acquisitions, the returns to acquisitive firms lag the market (Damodaran 2004).

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[32] Other studies, such as Capps (2005) and Sari (2002), examine whether acquisitions led to higher quality, generally finding no significant effect. See Town and Vogt (2006) for a review of the literature on acquisitions and quality.

[33] Nakamura (2006) studies why some acquisitions are more successful in increasing referrals than others and finds that referrals are likely to increase when the acquirer does not face capacity constraints and the target faces little competition. Even absent those conditions, however, an acquisition could be justified if the hospitals are close competitors in non-tertiary care or substantial efficiencies, perhaps from clinical integration or improved management, are likely.

We study several mechanisms by which a sophisticated acquirer might increase the profitability of a new stream of patients from the target market, as compared to simply increasing referrals across-the-board. The acquirer could focus on increasing referrals of patients undergoing particularly profitable procedures, patients with more generous insurance, or relatively healthy patients (who have lower expected costs of care). When we focus our attention on hospitals that successfully increase referrals, we find that they do so in ways consistent with the first two selection mechanisms. However, we find no evidence of selection based on severity.

The increase in referrals could improve welfare if the acquirers are superior in quality. The acquisition and subsequent change in referrals could also increase quality if the resulting consolidation of surgical volume facilitates learning economies. Huckman (2006) reports that there is no statistical significant change in the mortality rate in the entire state of New York after the wave of vertical integration. That analysis may be too broad, however, to identify effects in the fraction of acquisitions that resulted in changes in referral patterns. Integration could also harm patients by directing them to hospitals that would not select, based on location or other idiosyncratic reasons, absent the acquisitions.

The evidence of selective referrals is also potentially disturbing. Unless vertical integration creates efficiencies or improves outcomes – both of which have been hard to document in the literature – then integration is a zero sum game at best. The fact that some acquiring hospitals can increase profits through selective referrals implies that others will suffer losses. Hospitals with a worsening payer mix may have to reduce staffing and make other choices that threaten quality. They may also feel obliged to find their own targets, leading to a kind of market Balkanization in which patients face increasing restrictions on their choice of tertiary care hospital.

Appendices

Table A1. Tertiary DRGs

DRG	Description	Case-weight	% Offering DRG		Total Volume in DRG	
			Acq.	Targ.	Acq.	Targ.
1	CRANIOTOMY AGE >17 EXCEPT FOR TRAUMA	3.10	87%	17%	2,690	310
10	NERVOUS SYSTEM NEOPLASMS W CC	1.20	78%	27%	877	386
18	CRANIAL & PERIPHRL NERV DISORDERS W CC	0.94	57%	20%	544	325
75	MAJOR CHEST PROCEDURES	3.11	91%	40%	1,922	506
76	OTHER RESP SYSTEM O.R. PROCEDURES W CC	2.72	83%	50%	1,022	712
104	CARD VLV/OTR CARDITHOR O.R. W CARD CATH	7.24	74%	3%	1,893	35
105	CARD VLV/OTR CARDITHOR O.R. W/O CAR CATH	5.66	70%	0%	1,632	1
106	OTH PERM PACM IMPL/PTCA W COR STNT IMPLT	7.33	78%	0%	5,607	0
107	CORONARY BYPASS WITH CARDIAC CATH	5.46	74%	0%	4,553	0
110	MAJOR CARDIOVASC. PROCS.W CC	4.16	87%	33%	2,211	441
112	PERCUTANEOUS CARDIOVASC. PROCS.	1.92	87%	10%	13,919	196
116	OTH PERM PACM IMPL/PTCA W ART STNT IMPLT	2.47	96%	63%	2,473	1,009
120	OTHER CIRC. SYSTEM O.R. PROCs.	2.01	87%	37%	994	794
124	CIRC DISOR EX AMI W CARD CATH & CMPLX DX	1.40	96%	43%	6,009	2,040
125	CIRC DIS EX AMI W CARD CATH W/O CMPLX DX	1.04	96%	40%	5,281	739
144	OTHER CIRCULATORY SYSTEM DIAG W CC	1.15	96%	53%	2,202	839
257	TOTAL MASTECTOMY FOR MALIGNANCY W CC	0.91	74%	23%	803	369
290	THYROID PROCEDURES	0.92	78%	17%	1,025	326
315	OTHR KIDNEY/URINARY TRACT O.R. PROCS	2.07	78%	30%	1,007	550
331	OTHR KIDNY/URINARY TRCT DIAG AGE>17 W CC	1.02	74%	23%	1,100	424
358	UTERINE/ADNEX PR FOR NON-MALIG. W CC	1.24	91%	73%	3,215	1,537
360	VAGINA, CERVIX &VULVA PROCEDURES	0.88	57%	7%	592	239
370	CESAREAN SECTION W CC	1.10	87%	57%	4,385	1,574
371	CESAREAN SECTION W/O CC	0.72	87%	63%	9,112	6,725
372	VAGINAL DELIVERY W COMPLICATING DIAGS	0.59	87%	53%	5,397	1,982
376	POSTPARTUM/POST ABORT DIAG WO O.R. PROC	0.53	65%	20%	630	361
383	OTHR. ANTEPARTUM DIAG W MED COMP.	0.53	87%	60%	3,461	2,103
386	EXTREME IMMATURITY/RESP DIS SYN NEONATE	4.54	61%	17%	1,179	391
387	PREMATURITY W MAJOR PROBLEMS	3.10	74%	20%	1,754	505
388	PREMATURITY W/O MAJOR PROBLEMS	1.87	87%	43%	1,870	735
389	FULL TERM NEONATE W MAJOR PROBLEMS	1.84	87%	60%	5,207	2,795
390	NEONATE W OTHER SIGNIFICANT PROBLEMS	1.60	87%	57%	7,585	3,468
395	RED BLOOD CELL DISORDERS AGE >17	0.82	96%	63%	2,467	1,644
403	LYMPHOMA/NON-ACUTE LEUKEMIA W CC	1.72	70%	33%	1,015	499
410	CHEMO. WO ACUTE LEUKEMIA SEC DIAG	0.90	91%	57%	9,844	2,007
442	OTHER O.R. PROCEDURES FOR INJURIES W CC	2.25	57%	7%	565	222
466	AFTERCARE W/O HISTORY MALIGNCY SEC DIAG	0.71	13%	0%	302	44
478	OTHER VASCULAR PROCEDURES W CC	2.35	96%	67%	3,384	1,447
483	TRACHEOSTOMY EXCEPT FACE/MOUTH/NECK	16.12	91%	43%	1,804	710
486	OTHER O.R. PROC MULT SIGNIFICANT TRAUMA	4.90	22%	0%	339	40
500	BACK/NECK PROC EXCPT SPINAL FUSION WO CC	0.98	0	0	0	0

Note: Hospitals treating at least 20 patients in a DRG are defined as "offering" that service.

Source: 1994 Florida discharge data and 1995 New York discharge data.

Appendix B. A Quantile Model

Let *C* denote total list charges for a patient admitted to the acquiring hospital:

$$C_i = X_i b + e_i.$$

For illustration, consider the probability of patient *i*'s charges falling in the 90th percentile:

$$\Pr(X b_{(90)} + e < p_{(90)}) = .9$$
$$\Pr(e < p_{(90)} - X b_{(90)}) = .9$$
$$F(p_{(90)} - X b_{(90)}) = .9, \text{ for the CDF, } F, \text{ of } e.$$
$$p_{(90)} - X b_{(90)} = F^{-1}(.9)$$

The estimator is

$$\hat{b}_{90} = \underset{b \in}{\arg\min} \sum_{i=1}^{N} \left[.90 - 1\left(\text{Charges}_i - X b < 0\right)\right]\left[\text{Charges}_i - X b\right],$$

The first term in brackets equals .9 when (Charges>*Xβ*) and equals (-.1) when (Charges< *Xβ*), so the entire sum to be minimized consists of all positive numbers, as indicated by analogy to the Least Absolute Deviations (LAD) estimator for the median. The minimization above adjusts the betas to increase *Xβ* if *C* exceeds more than 90% of the *Xβ*'s, and vice-versa if *C* is smaller than 90% of the *Xβ*'s. For example, at $\hat{b}_{(90)}$, 90% of the residuals, ε = *Charges* – *Xβ* will be positive and 10% will be negative.

Appendix C. Linear Probability Model Results

To examine potential selection bias stemming from our algorithm for selecting control zip codes, we also estimate the acquisition effects (b_{TA}^{LPM}) using a linear probability model (LPM) and all potential control zip codes. For comparison, we also estimate the same linear probability models using the same control zip codes as in the primary Logit estimations. When we use all potential zip codes, we obtain larger and more significant coefficients in several markets. However, the general pattern remains that there are more positive than negative significant effects.

Table A2. Linear Probability Model Results: All Potential Controls and Selected Controls

			b_{TA}^{LPM} Estimates			
			CABG/PTCA		Tertiary	
St.	Acquirer	Target	*Logit Control Zip Codes*	*All Potential Control Zip Codes*	*Logit Control Zip Codes*	*All Potential Control Zip Codes*
FL	Halifax	Bert Fish	-0.054*	-0.092***	0.026	0.050***
FL	Orlando Reg.	Parrish	[a]	-0.081***	-0.013	-0.026***
FL	Orlando Reg.	South Seminole	-0.048	0.051	-0.177	-0.179***
NY	Buffalo Gen.	DeGraff	0.059**	0.052***	0.037***	0.051***
NY	Crouse Hosp.	Community Gen.	[b]	[b]	0.004	0.011
NY	Ellis Hosp.	Amsterdam	0.236***	0.472***	0.043**	0.089***
NY	Mt. Sinai/NYU	Western Queens	-0.007	0.010	-0.009***	-0.039***
NY	North Shore Univ.	Southside	0.083***	0.101***	0.039***	0.061***
NY	NYU	Downtown	[a]	-0.017	0.011	-0.018**
NY	Rochester Gen.	Myers Comm.	[c]	[c]	0.066**	0.145***
NY	St. Francis	Mercy MC	0.040	0.037	0.016**	0.042***
NY	Strong Memorial	Highland	-0.072	-0.100***	-0.018	-0.050***
NY	United Health	Delaware Valley	[a]	[a]	0.025	0.098***
NY	Winthrop Univ.	Mid-Island	0.018	0.076***	-0.004	0.022***
NY	Winthrop Univ.	South Nassau	0.001	0.006	0.011**	0.018***
FL	Morton Plant	North Bay	[a]	-0.028	[a]	-0.027**
FL	Orlando Reg.	Leesburg Reg.	[d]	[d]	[b]	[b]
FL	University Comm.	Helen Ellis	[b]	[b]	[b]	[b]
NY	New York Hosp	Little Neck	[b]	[b]	[b]	[b]
NY	New York Hosp	Wyckoff Heights	0.006	0.006	[b]	[b]
NY	North Shore Univ.	Staten	[b]	[b]	[b]	[b]
NY	NY Presb.	Brooklyn	-0.020	0.007	[b]	[b]
NY	St. Francis	Good Sam. Hosp.	[b]	[b]	[b]	[b]
NY	St. Francis	Good Sam. MC	0.058**	0.062**	[a]	0.005
NY	St. Francis	St. Charles	[a]	-0.004	[b]	[b]
NY	St. Luke's	Long Island	[b]	[b]	[b]	[b]
		# Positive	4	5	6	9
		# Negative	1	3	1	5
		# Insignificant	8	9	8	2
		Not Defined	13	9	11	10

[a] Fewer than 200 observations in control market.
[b] Acquirer's share in target market below 5% before and after acquisition.
[c] Acquirer's share in target market above 95% before and after acquisition.
[d] Leesburg Regional Hospital began offering CABG and PTCA shortly after being acquired.

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Figure 1: Two Representative Acquisitions

Mt. Sinai Acquires Western Queens: CABG/PTCA

NY Presb. Acquires Brooklyn Hospital: CABG/PTCA
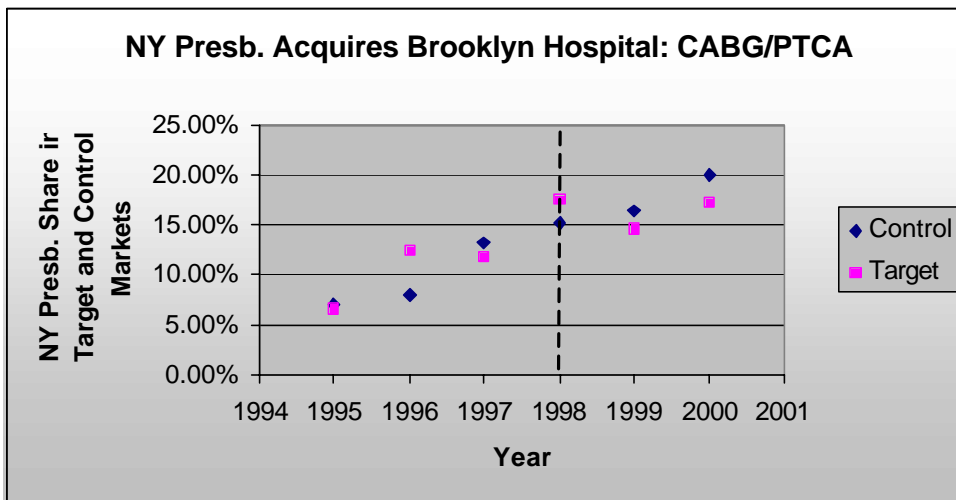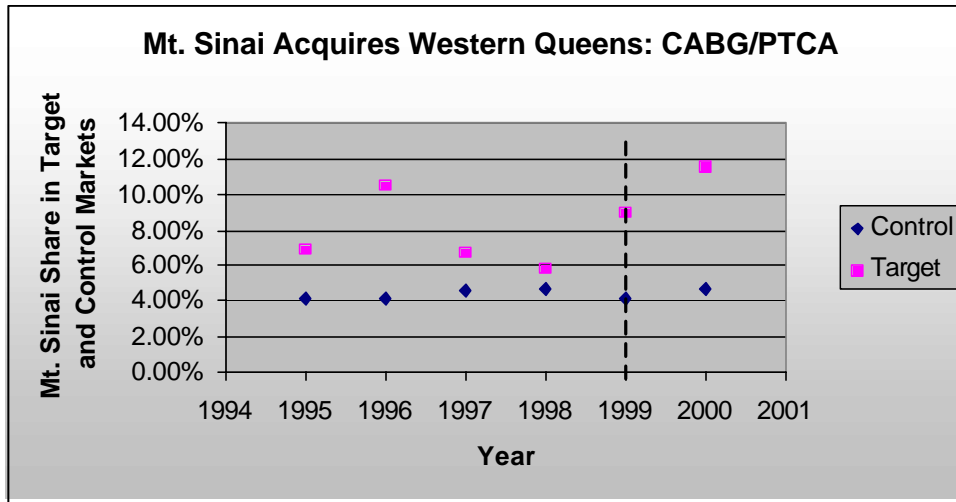
Figure 2: Selecting the Candidate Control Region

Potential Control Markets

A

T
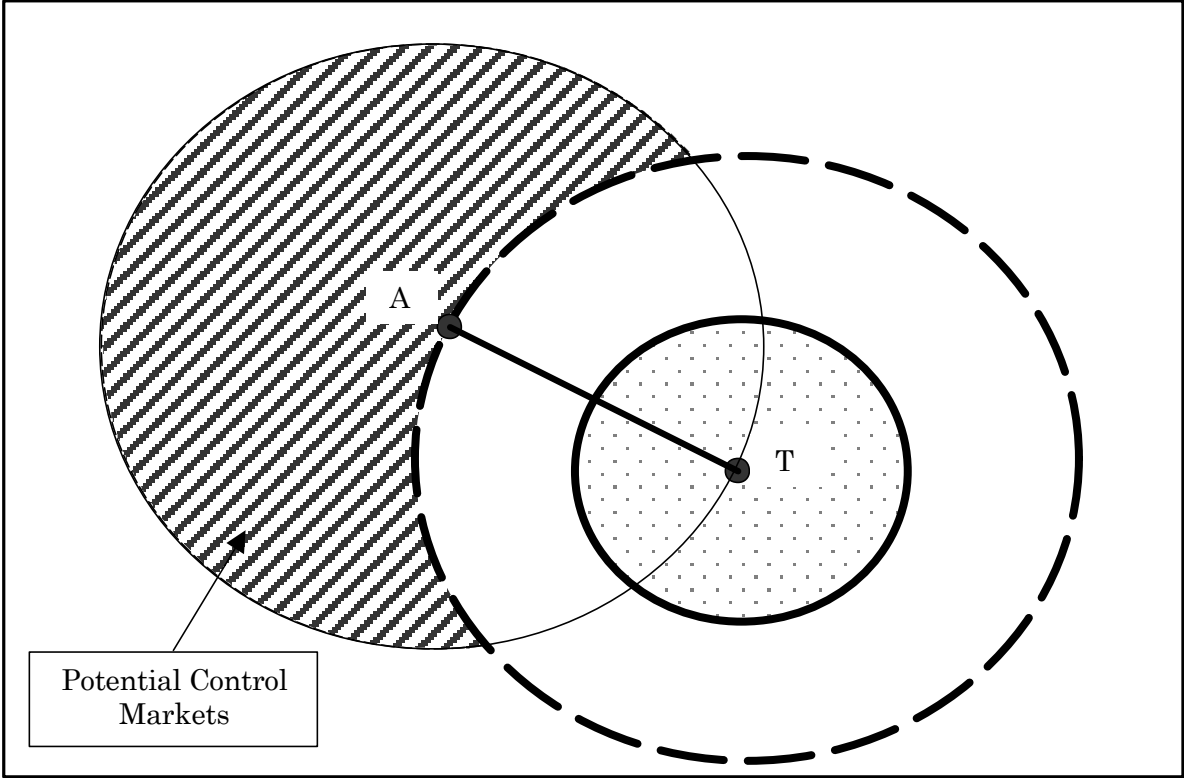
Figure 3: Criteria for Matching Target and Control Zip Codes

CABG & PTCA		Tertiary DRGs	
Acquirer's Share In The Target Market Is	Maximum Share Difference	Acquirer's Share In The Target Market Is	Maximum Share Difference
> 5%	0.050	> 40%	0.10
< 5%	0.025	30% to 40%	0.08
		20% to 30%	0.06
		10% to 20%	0.04
		5% to 10%	0.02
		<5%	0.01

Table 1. Hospital Summary Statistics

	Florida			
	Acquirers (N=5)		Targets (N=6)	
	Mean	S.D.	Mean	S.D.
Government	0.25	0.45	0.29	0.46
Non-Profit	0.75	0.45	0.46	0.51
For-Profit	0.00	0.00	0.25	0.44
COTH	0.25	0.45	0.00	0.00
Open Heart	0.88	0.34	0.08	0.28
Beds	662.06	310.75	203.00	104.39
Admissions	30,607	15,573	7,690	3,371
IP Days - Total	146,220	75,926	41,415	26,925
IP Days - Medicare	57,150	22,726	23,961	14,519
IP Days - Medicaid	20,976	15,420	6,403	8,975

	New York			
	Acquirers (N=14)		Targets (N=20)	
	Mean	S.D.	Mean	S.D.
Government	0.00	0.00	0.00	0.00
Non-Profit	1.00	0.00	0.95	0.22
For-Profit	0.00	0.00	0.05	0.22
COTH	0.71	0.46	0.10	0.31
Open Heart	0.88	0.33	0.05	0.22
Beds	777.09	535.12	304.77	162.47
Admissions	32,057	18,079	12,391	7,583
IP Days - Total	235,062	154,047	84,973	47,924
IP Days -Medicare	89,719	46,570	38,196	21,126
IP Days - Medicaid	48,209	48,538	19,669	17,742

Notes:
1. Acquirers outnumber targets due to several acquirers acquiring multiple hospitals.
2. Averages are computed using the entire sample period.

Table 2. Patient Summary Statistics

	New York							
	CABG/PTCA				Tertiary DRGs			
	Control		*Target*		*Control*		*Target*	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medicare	0.491	0.250	0.482	0.250	0.241	0.183	0.229	0.177
Uninsured	0.025	0.024	0.023	0.022	0.049	0.047	0.055	0.052
Medicaid	0.096	0.087	0.090	0.082	0.307	0.213	0.298	0.209
Fee for Service	0.122	0.107	0.120	0.106	0.119	0.105	0.133	0.115
Blue Cross	0.121	0.107	0.128	0.112	0.113	0.100	0.124	0.108
HMO	0.144	0.124	0.157	0.132	0.170	0.141	0.162	0.136
White	0.686	0.215	0.702	0.209	0.398	0.240	0.459	0.248
Black	0.045	0.043	0.068	0.064	0.232	0.178	0.276	0.200
Hispanic	0.050	0.048	0.058	0.055	0.141	0.121	0.112	0.099
Other race	0.114	0.101	0.071	0.066	0.144	0.123	0.107	0.095
Unknown race	0.106	0.094	0.101	0.091	0.084	0.077	0.046	0.044
Female	0.298	0.209	0.318	0.217	0.636	0.231	0.634	0.232
Age	66.440	11.030	65.410	10.920	40.40	27.280	39.750	26.800
#Procedure	6.407	3.356	6.438	3.457	2.722	2.539	2.807	2.584
#Diagnoses	6.685	3.406	6.649	3.382	4.730	2.935	4.719	2.938

	Florida							
	CABG/PTCA				Tertiary DRGs			
	Control		*Target*		*Control*		*Target*	
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Medicare	0.514	0.250	0.574	0.244	0.354	0.229	0.399	0.240
Uninsured	0.037	0.035	0.032	0.031	0.046	0.044	0.039	0.037
Medicaid	0.018	0.017	0.016	0.016	0.173	0.143	0.136	0.117
Fee for Service	0.126	0.110	0.088	0.080	0.115	0.102	0.113	0.100
PPO	0.110	0.098	0.141	0.121	0.136	0.117	0.144	0.123
HMO	0.195	0.157	0.149	0.127	0.176	0.145	0.170	0.141
White	0.934	0.062	0.929	0.066	0.781	0.171	0.864	0.117
Black	0.019	0.019	0.022	0.021	0.100	0.090	0.071	0.066
Hispanic	0.022	0.022	0.019	0.019	0.083	0.076	0.034	0.033
Other race	0.012	0.012	0.011	0.011	0.021	0.020	0.015	0.015
Unknown race	0.012	0.012	0.019	0.018	0.015	0.014	0.016	0.016
Female	0.310	0.214	0.324	0.219	0.573	0.245	0.563	0.246
Age	65.260	11.140	66.050	11.320	46.130	27.750	48.740	27.260

Notes:
1. In New York, PPO patients are not separately identified from FFS patients.
2. In Florida, Blue Cross patients are not separately identified from other PPO patients.
3. Florida does not record the number of procedures or the number of diagnoses.
4. Averages are computed using the entire sample period.

Table 3. Raw Difference-in-Difference Estimates

	Average ($?Share^{Target} - ?Share^{Control}$)	
	Sample (N = 26)	
Model	*CABG/PTCA*	*Tertiary*
No Year Effects	-0.0252	-0.0125
	(0.0562)	(0.0275)
Year Effects	-0.0252	-0.0125
	(0.0550)	(0.0275)
Year & State Effects	-0.0252	-0.0125
	(0.0544)	(0.0275)

Standard errors in parentheses.

Table 4. Acquisition Effects for CABG/PTCA Referrals, All Payers

St.	Acquirer	Target	# Target	# Control	Avg. Share, Pre-Acq.	b_{TA}	*Marginal Effect*
FL	Halifax	Bert Fish	2,271	1,016	24%	-0.296	-0.031
FL	Orlando Reg.	South Seminole	5,634	598	12%	-0.357	-0.031
NY	Buffalo Gen.	DeGraff	3,499	1,534	85%	0.778***	0.046***
NY	Ellis Hosp.	Amsterdam	1,017	534	51%	0.498***	0.311***
NY	Mt. Sinai/NYU	Western Queens	5,875	887	16%	-0.061	-0.004
NY	New York Hosp.	Wyckoff Heights	3,042	7,620	0%	0.707**	0.025**
NY	North Shore Univ.	Southside	2,147	10,101	8%	0.811***	0.071***
NY	NY Presb.	Brooklyn	5,152	4,257	10%	-0.187	-0.014
NY	St. Francis	Good Sam. MC	3,330	1,802	27%	0.274**	0.061**
NY	St. Francis	Mercy MC	3,267	278	59%	0.170	0.037
NY	Strong Memorial	Highland	1,492	225	22%	-0.424	-0.078
NY	Winthrop Univ.	Mid-Island	3,241	1,129	27%	0.082	0.018
NY	Winthrop Univ.	South Nassau	3,517	10,628	8%	0.006	0.000
FL	Morton Plant[+]	North Bay					
FL	Orlando Reg.[‡]	Leesburg Reg.					
FL	Orlando Reg.[+]	Parrish					
FL	University Comm.[++]	Helen Ellis					
NY	Crouse Hosp.[++]	Community Gen.					
NY	New York Hosp.[++]	Little Neck					
NY	North Shore Univ.[++]	Staten					
NY	NYU[+]	Downtown					
NY	Rochester Gen.[+++]	Myers Comm.					
NY	St. Francis[++]	Good Sam. Hosp.					
NY	St. Francis[+]	St. Charles					
NY	St. Luke's[++]	Long Island					
NY	United Health[+]	Delaware Valley					

b_{TA} is the estimated Logit coefficient on the indicator for the post-acquisition target group.

Marginal Effect $= E(Y_{i,t} \mid X_{i,t}, \text{Market=T, t=Post}) - E(Y_i \mid X_{i,t}, \text{Market=T, t=Pre})$. This is evaluated at the median of all continuous variables and the modal value of all discrete variables.

+ Control Market not definable.

++ Acquirer's share in target market below 5%, before and after acquisition.

+++ Acquirer's share in target market above 95%, before and after acquisition.

‡ Leesburg Regional Hospital began offering CABG and PTCA shortly after being acquired.

*** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Table 5. Acquisition Effects for Tertiary Referrals, All Payers

St.	Acquirer	Target	# Target	# Control	Avg. Share, Pre-Acq.	b_{TA}	Marginal Effect
FL	Halifax	Bert Fish	16,741	6,192	20%	0.203**	0.011**
FL	Orlando Reg.	Parrish	23,713	12,094	8%	-0.413***	-0.010***
FL	Orlando Reg.	South Seminole	40,775	8,344	16%	-1.571***	-0.166***
NY	Buffalo Gen.	DeGraff	38,765	22,877	49%	0.174***	0.038***
NY	Crouse Hosp.	Community Gen.	28,233	12,446	38%	0.0200	0.003
NY	Ellis Hosp.	Amsterdam	9,548	442	21%	0.320**	0.079**
NY	Mt. Sinai/NYU	Western Queens	67,164	32,836	6%	-0.325***	-0.014***
NY	North Shore Univ.	Southside	31,907	68,093	5%	0.693***	0.049***
NY	NYU	Downtown	12,644	32,843	10%	0.129	0.013
NY	Rochester Gen.	Myers Comm.	3,227	27,019	33%	0.335*	0.079*
NY	St. Francis	Mercy MC	36,786	17,792	13%	0.125*	0.030*
NY	Strong Memorial	Highland	23,659	6,977	29%	-0.082	-0.017
NY	United Health	Delaware Valley	7,593	484	21%	0.183	0.038
NY	Winthrop Univ.	Mid-Island	39,624	14,282	19%	-0.027	-0.006
NY	Winthrop Univ.	South Nassau	46,096	22,697	11%	0.124**	0.007**
FL	Morton Plant[+]	North Bay					
FL	Orlando Reg.[++]	Leesburg Reg.					
FL	University Comm.[++]	Helen Ellis					
NY	New York Hosp[++]	Little Neck					
NY	New York Hosp[++]	Wyckoff Heights					
NY	North Shore Univ.[++]	Staten					
NY	NY Presb.[++]	Brooklyn					
NY	St. Francis[+, ++]	Good Sam. Hosp.					
NY	St. Francis[+]	Good Sam. MC					
NY	St. Francis[+, ++]	St. Charles					
NY	St. Luke's[++]	Long Island					

b_{TA} is the estimated Logit coefficient on the indicator for the post-acquisition target group.

Marginal Effect $= E(Y_{i,t} \mid X_{i,t},$ Market=T, t=Post)$- E(Y_i \mid X_{i,t},$ Market=T, t=Pre). This is evaluated at the median of all continuous variables and the modal value of all discrete variables.

+ Control Market not definable.

++ Acquirer's share in target market below 5%, before and after acquisition.

+++ Acquirer's share in target market above 95%, before and after acquisition.

*** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Table 6. Acquisition Marginal Effects by Payer Category, CABG/PTCA

St.	Acquirer	Target	# Target	# Control	FFS/PPO	Medicare	HMO	Medicaid/ Indigent
FL	Halifax	Bert Fish	2,271	1,016	-0.008	-0.038	-0.0370	-0.035
FL	Orlando Reg.	South Seminole	5,634	598	0.004	-0.026	-0.076	0.001
NY	Buffalo Gen.	DeGraff	3,499	1,534	0.080	0.047**	0.028	--
NY	Ellis	Amsterdam	1,017	534	0.343*	0.287***	0.423**	--
NY	Mt. Sinai/NYU	Western Queens	5,875	887	-0.021	-0.011	-0.005	0.019
NY	New York Hosp	Wyckoff Heights	3,042	7,620	0.029	0.036**	0.022	0.034
NY	North Shore Univ.	Southside	2,147	10,101	0.072**	0.041**	0.115**	0.037
NY	NY Presb.	Brooklyn	5,152	4,257	0.040	-0.034***	-0.045	0.059
NY	St. Francis	Mercy MC	3,267	278	-0.069	0.045	0.284***	0.151
NY	St. Francis	Good Sam. MC	3,330	1,802	-0.028	0.068*	0.229**	0.097
NY	Strong Memorial	Highland	1,492	225	0.139	-0.094	-0.043	-0.201
NY	Winthrop	Mid-Island	3,241	1,129	0.195*	0.019	-0.139	0.348
NY	Winthrop	South Nassau	3,517	10,628	0.004	-0.006	-0.002	0.159**
FL	Morton Plant[+]	North Bay						
FL	Orlando Reg.[‡]	Leesburg Reg.						
FL	Orlando Reg.[+]	Parrish						
FL	University Comm.[++]	Helen Ellis						
NY	Crouse[++]	Community Gen.						
NY	New York Hosp[++]	Little Neck						
NY	North Shore Univ.[++]	Staten						
NY	NYU[+]	Downtown						
NY	Rochester Gen.[+++]	Myers Comm.						
NY	St. Francis[+]	St. Charles						
NY	St. Francis[++]	Good Sam. Hosp						
NY	St. Luke's[++]	Long Island						
NY	United Health[+]	Delaware Valley						

Marginal Effect $= E(Y_{i,t} \mid X_{i,t}, \text{Market=T, t=Post}) - E(Y_i \mid X_{i,t}, \text{Market=T, t=Pre})$. This is evaluated at the indicated value of the payer variable, the median of all continuous variables and the modal value of other discrete variables.

+ Control Market not definable.

++ Acquirer's share in target market below 5%, before and after acquisition.

+++ Acquirer's share in target market above 95%, before and after acquisition.

‡ Leesburg Regional Hospital began offering CABG and PTCA shortly after being acquired.

*** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Table 7. Acquisition Marginal Effects by Payer, Tertiary DRGs

St.	Acquirer	Target	# Target	# Control	FFS/PPO	Medicare	HMO	Medicaid/ Indigent
FL	Halifax	Bert Fish	16,741	6,192	0.026	0.020***	-0.005	0.012
FL	Orlando Reg.	Parrish	23,713	12,094	-0.003*	0.013***	0.004	-0.008***
FL	Orlando Reg.	South Seminole	40,775	8,344	-0.157***	-0.069***	-0.205***	-0.198***
NY	Buffalo Gen.	DeGraff	38,765	22,877	0.052	0.010	0.079	-0.208**
NY	Crouse	Community Gen.	28,233	12,446	0.007	0.022*	-0.052	0.057
NY	Ellis	Amsterdam	9,548	442	0.151	0.072*	-0.047	0.143
NY	Mt. Sinai/NYU	Western Queens	67,099	32,901	-0.030**	-0.011***	-0.018	-0.006
NY	North Shore Univ.	Southside	31,927	68,073	0.060**	0.076***	0.060*	0.068**
NY	NYU	Downtown	12,644	32,843	0.039	0.005	--	-0.017
NY	Rochester Gen.	Myers Comm.	3,227	27,019	0.143	0.182***	-0.007	-0.085
NY	St. Francis	Mercy MC	36,786	17,792	-0.042	0.047***	0.177**	0.083
NY	Strong Memorial	Highland	23,659	6,977	0.139*	-0.004	-0.072	0.011
NY	United Health	Delaware Valley	7,593	484	0.120	0.108***	0.013	-0.045*
NY	Winthrop	Mid-Island	39,624	14,282	0.087	0.029	-0.108**	-0.014
NY	Winthrop	South Nassau	46,096	22,697	0.026*	0.014***	-0.012*	0.030*
FL	Morton Plant[+]	North Bay						
FL	Orlando Reg.[++]	Leesburg Reg.						
FL	University Comm.[++]	Helen Ellis						
NY	New York Hosp.[++]	Little Neck						
NY	New York Hosp.[++]	Wyckoff Heights						
NY	North Shore Univ.[++]	Staten						
NY	NY Presb.[++]	Brooklyn						
NY	St. Francis[++]	Good Sam. Hosp.						
NY	St. Francis[+]	Good Sam. MC						
NY	St. Francis[++]	St. Charles						
NY	St. Luke's[++]	Long Island						

Marginal Effect $= E(Y_{i,t} \mid X_{i,t}, \text{Market=T, t=Post}) - E(Y_i \mid X_{i,t}, \text{Market=T, t=Pre})$. This is evaluated at the indicated value of the payer variable, the median of all continuous variables and the modal value of other discrete variables.

+ Control Market not definable.

++ Acquirer's share in target market below 5%, before and after acquisition.

+++ Acquirer's share in target market above 95%, before and after acquisition.

*** Significant at 1%; ** Significant at 5%; * Significant at 10%.

Table 8. Summary of Marginal Effects, by Payer Type

	CABG/PTCA					Tertiary					Tertiary, Excluding CABG/PTCA			
Payer Class	> 0	< 0	= 0[a]	Undef.[b]		> 0	< 0	= 0[a]	Undef.[b]		> 0	< 0	= 0[a]	Undef.[b]
FFS/PPO	3	0	17	6		3	3	18	2		4	3	17	2
Medicare	5	1	14	6		9	2	13	2		6	2	16	2
HMO	4	0	16	6		2	3	18	3		1	4	18	3
Medicaid/Indigent	1	0	17	8		2	4	18	2		3	3	18	2
	Any +	Any -	All 0	Undef.		Any +	Any -	All 0	Undef.		Any +	Any -	All 0	Undef.
Total:	8	1	11	6		10	7	10	2		7	6	12	2

Notes   [a] Includes insignificant results as well as cases where the acquirer's share was above 5% or below 95% both pre and post acquisition.

           [b] Includes instances where the control market was undefinable or where the particular payer-specific effect was not estimable.

Table 9. Quantile Regression Results: Acquisition Effects on CABG/PTCA List Charges

St.	Acquirer	Target	# Control	# Target	Mean Effect	.10	.25	.50	.75	.90
								Medicare		
FL	Halifax	Bert Fish	675	275	0.129**	-0.005	0.073	0.194***	0.132	0.150
FL	Orlando Reg.	South Seminole	125	351	-0.090	0.109	-0.150	-0.104	-0.106	-0.094
NY	Buffalo Gen.	DeGraff	3,202	2,282	0.059*	-0.044	-0.006	-0.011	0.039	0.240***
NY	Ellis	Amsterdam	1,188	458	0.038	-0.013	0.004	-0.010	-0.007	0.142
NY	Mt. Sinai/NYU	Western Queens	312	335	-0.090	-0.382**	-0.065	0.015	-0.155	-0.012
NY	NY Presb.	Brooklyn	910	322	0.060	-0.224***	-0.019	0.115	0.256*	0.537**
NY	Rochester Gen.	Myers Comm.	5,432	261	0.067	0.150***	0.150***	0.101**	0.078	-0.095
NY	St. Francis	Good Sam. MC	960	677	0.149***	0.155***	0.111***	0.157***	0.162**	0.078
NY	St. Francis	Mercy MC	960	1,294	0.135***	0.168***	0.091***	0.063	0.089	0.200**
NY	St. Francis	St. Charles	926	334	0.087	0.014	-0.011	0.131**	0.211***	0.321**
NY	Strong Mem.	Highland	334	223	0.148	0.090	0.104	0.134**	0.206	0.250
NY	United Health	Delaware Valley	1,187	300	0.125*	0.189**	0.183***	0.103	0.115	-0.112
NY	Winthrop	Mid-Island	890	655	0.228***	0.147***	0.166***	0.212***	0.146*	0.383***
NY	Winthrop	South Nassau	1,634	195	0.225***	0.217***	0.161**	0.205***	0.121	0.106
								HMO		
FL	Halifax	Bert Fish	675	275	0.164	0.041	0.108	0.213	0.208	0.158
FL	Orlando Reg.	South Seminole	125	351	-0.039	0.124	-0.042	-0.113	0.015	-0.139
NY	Buffalo Gen.	DeGraff	3,202	2,282	0.037	-0.010	0.021	0.019	0.058	0.056
NY	Ellis	Amsterdam	1,188	458	-0.042	-0.039	-0.029	0.016	0.058	0.008
NY	Mt. Sinai/NYU	Western Queens	312	335	0.047	-0.245	-0.028	0.017	-0.014	0.057
NY	NY Presb.	Wyckoff Heights	698	114	0.271	--	--	--	--	--
NY	Rochester Gen.	Brooklyn	910	322	0.086	-0.157	0.061	0.121	0.055	0.228
NY	St. Francis	Myers Comm.	5,432	261	0.180	0.195	0.202	0.102	0.213	0.029
NY	St. Francis	Good Sam. MC	960	677	0.037	0.108	0.059	0.037	0.036	-0.046
NY	St. Francis	Mercy MC	960	1,294	0.081	0.164	0.042	0.050	0.123	0.093
NY	Strong Mem.	St. Charles	926	334	-0.042	-0.013	-0.012	-0.014	0.017	0.029
NY	United Health	Highland	334	223	0.232	-0.052	-0.008	0.231	0.361	0.366
NY	Winthrop	Delaware Valley	1,187	300	0.059	0.005	0.134	0.072	0.174	-0.074
NY	Winthrop	Mid-Island	890	655	0.225	0.175	0.250	0.245	0.180	0.305

Cutoff values for the .10, .25, .50, .75, and .90 deciles

Table 10. Quantile Regression Results: Acquisition Effects on Tertiary List Charges

						Cutoff values for the .10, .25, .50, .75, and .90 deciles				
					Mean	**Medicare**				
St.	Acquirer	Target	# Cont.	# Targ.	Effect	.10	.25	.50	.75	.90
FL	Morton Plant	North Bay	4,523	1,131	0.145***	0.203***	0.179***	0.128***	0.116***	0.079
FL	Orlando Reg.	Parrish	4,610	221	0.117	0.145*	0.022	0.079	0.075	-0.002
FL	Orlando Reg.	South Seminole	4,004	491	0.122**	0.149**	0.069	0.144**	0.203***	0.172
NY	Buffalo Gen.	Columbus	1,663	189	-0.144	-0.021	-0.017	-0.135	-0.144	-0.210
NY	Buffalo Gen.	DeGraff	14,833	14,212	0.066***	0.040*	0.072***	0.044***	0.055**	0.163***
NY	Crouse	Community Gen.	3,829	4,977	0.058	0.141***	0.079***	0.062	-0.002	-0.070
NY	Ellis	Amsterdam	4,243	1,459	-0.081	-0.019	-0.029	-0.027	0.045	-0.074
NY	Mt. Sinai/NYU	Western Queens	6,028	3,008	-0.171***	-0.033	-0.005	-0.124**	-0.210***	-0.339***
NY	New York Hosp	Little Neck	7,456	114	0.262	0.238	0.236	0.045	0.244	0.130
NY	New York Hosp	Wyckoff Heights	7,456	559	0.164**	0.166*	0.098	0.056	0.077	0.098
NY	North Shore Un.	Southside	14,584	583	0.151	0.195***	0.137*	0.150*	0.140	0.166
NY	NYU	Downtown	2,146	612	0.216**	0.192*	0.200**	0.090	-0.005	0.240
NY	Strong Memorial	Highland	4,044	3,950	-0.004	0.011	0.055	0.011	0.055	0.057
NY	NY Presb.	Brooklyn	9,500	1,864	0.096*	0.113**	0.152***	0.096**	0.100*	0.102
NY	Rochester Gen.	Myers Comm.	25,675	972	-0.010	0.038	0.019	0.034	0.009	-0.094
NY	United Health	Delaware Valley	6,900	1,061	0.214***	0.215***	0.245***	0.197***	0.226***	0.223**
NY	St. Francis	Good Sam. MC	3,915	1,927	0.077**	0.080**	0.091***	0.097**	0.163***	0.007
NY	St. Francis	Mercy MC	3,995	3,822	0.137***	0.136***	0.148***	0.137***	0.130***	0.128**
NY	St. Francis	St. Charles	3,915	1,295	0.081**	0.086**	0.049	0.055	0.093*	0.182**
NY	St. Luke's	Long Island	5,199	186	0.120	0.275	0.337*	0.304***	0.017	-0.208
NY	Winthrop	Mid-Island	11,439	4,650	0.039	0.049	0.085***	0.000	0.014	0.180***
NY	Winthrop	South Nassau	13,893	2,702	0.074**	0.174***	0.144***	0.092***	-0.005	-0.012
						HMO				
FL	Morton Plant	North Bay	4,523	1,131	0.179	0.260	0.226	0.136	0.183	0.146
FL	Orlando Reg.	Parrish	4,610	221	0.104	-0.172	0.028	0.109	0.107	0.145
FL	Orlando Reg.	South Seminole	4,004	491	0.188	0.195	0.124	0.203	0.260	0.200
NY	Buffalo Gen.	Columbus	1,663	189	0.097	0.210	0.134	-0.036	-0.117	-0.060
NY	Buffalo/	DeGraff	14,833	14,212	0.038	-0.000	0.034	0.036	0.035	0.103
NY	Crouse	Community Gen.	3,829	4,977	-0.026	0.009	-0.028	-0.003	-0.038	-0.051
NY	Ellis	Amsterdam	4,243	1,459	-0.017	0.011	0.049	0.032	0.089	-0.061
NY	Mt. Sinai/NYU	Western Queens	6,028	3,008	-0.019	0.043	0.032	-0.072	-0.041	-0.071
NY	New York Hosp	Little Neck	7,456	114	0.161	0.150	0.054	0.004	0.304	0.319
NY	New York Hosp	Wyckoff Heights	7,456	559	0.145	0.006	0.107	0.113	0.148	0.247
NY	North Shore Un.	Southside	14,584	583	0.315	0.225	0.239	0.290	0.220	0.316
NY	NYU	Downtown	2,146	612	0.216	--	--	--	--	--
NY	Strong Memorial	Highland	4,044	3,950	0.015	-0.043	-0.017	0.043	0.094	0.138
NY	NY Presb.	Brooklyn	9,500	1,864	0.079	0.084	0.093	0.049	0.050	0.153
NY	Rochester Gen.	Myers Comm.	25,675	972	0.012	0.056	0.128	0.088	0.006	-0.054
NY	United Health	Delaware Valley	600	1,061	0.126	0.164	0.207	0.167	0.170	0.072
NY	St. Francis	Good Sam. MC	3,915	1,927	0.021	-0.006	-0.004	0.090	0.103	0.032
NY	St. Francis	Mercy MC	3,995	3,822	0.121	0.108	0.145	0.124	0.112	0.102
NY	St. Francis	St. Charles	3,915	1,295	-0.171	-0.108	-0.256	-0.104	-0.062	0.013
NY	St. Luke's	Long Island	5,199	186	0.120	--	--	--	--	--
NY	Winthrop	Mid-Island	11,439	4,650	0.207	0.112	0.138	0.160	0.190	0.205
NY	Winthrop	South Nassau	13,893	2,702	0.132	0.201	0.162	0.113	0.111	0.084

Table 11. Ordered Logit Results: Acquisition Effects on The Number Of Diagnoses

					Change in # Diagnoses	
					CABG/PTCA	
St.	Acquirer	Target	# Control	# Target	Medicare	HMO
NY	Buffalo Gen.	DeGraff	3,202	2,282	-0.102	0.015
NY	Ellis	Amsterdam	1,188	458	1.795***	0.904
NY	Mt. Sinai/NYU	Western Queens	312	335	0.574	0.828
NY	NY Presb.	Brooklyn	910	322	0.185	-0.349
NY	Rochester Gen.	Myers Comm.	5,432	261	0.195	0.286
NY	St. Francis	Good Sam. MC	960	677	0.410*	-0.152
NY	St. Francis	Mercy MC	960	1,294	0.360**	-0.042
NY	St. Francis	St. Charles	926	334	0.189	-0.093
NY	Strong Memorial	Highland	334	223	0.257	0.854
NY	United Health	Delaware Valley	1,187	300	-0.604*	-0.887
NY	Winthrop	Mid-Island	890	655	0.076	0.613
NY	Winthrop	South Nassau	1,634	195	0.547*	0.052
					Tertiary DRGs	
St.	Acquirer	Target	# Control	# Target	Medicare	HMO
NY	Buffalo Gen.	Columbus	2,114	230	0.019	-0.539
NY	Buffalo Gen.	DeGraff	15,151	14,472	0.130*	0.243
NY	Crouse	Community Gen.	3,966	5,140	0.345***	-0.004
NY	Ellis	Amsterdam	4,582	1,535	0.755***	0.603
NY	Mt. Sinai/NYU	Western Queens	6,211	3,104	0.350**	0.592
NY	New York Hosp	Little Neck	8,047	120	-0.337	-0.617
NY	New York Hosp	Wyckoff Heights	8,047	593	0.325	0.395
NY	North Shore Univ.	Southside	15,000	594	-0.198	0.102
NY	NY Presb.	Brooklyn	9,738	1,912	0.280**	0.395
NY	NYU	Downtown	2,370	655	-0.633***	--
NY	Rochester Gen.	Myers Comm.	26,255	990	0.250	0.302
NY	St. Francis	Good Sam. MC	4,154	1,968	-0.134	-0.367
NY	St. Francis	Mercy MC	4,170	3,912	-0.205*	-0.157
NY	St. Francis	St. Charles	4,154	1,324	0.084	-0.352
NY	St. Luke's	Long Island	5,585	198	0.254	--
NY	Strong Memorial	Highland	4,149	4,055	0.238**	0.034
NY	United Health	Delaware Valley	7,232	1,080	-0.165	0.186
NY	Winthrop	Mid-Island	11,660	4,724	0.043	0.182
NY	Winthrop	South Nassau	14,145	2,739	-0.209**	-0.117

Notes:
1. Estimates based on results from an Ordered Logit model.
2. Florida data do not report the number of diagnoses.

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