The Impact of Market Forces and Public Health Insurance on Inpatient Care

by

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Abstract

This dissertation considers both private and public-sector influences on inpatient care, focusing first on the impact of strategic hospital behavior on entry into new procedure markets, and second on the effect of changes in Medicaid and Medicare on hospital care. Chapter 1, "Entry Deterrence in Hospital Procedure Markets: A Simple Model of Learning-by-Doing," investigates whether incumbent hospitals threatened by entry in profitable procedure markets take advantage of learning-by-doing in these markets to erect barriers to entry. By focusing on incumbent behavior following a positive shock to the profitability of a procedure, and comparing this behavior across markets with different levels of entry-deterrence incentives, I am able to detect limited evidence consistent with entry deterrence through learning-by-doing in three case studies: electrophysiological studies, liver transplants, and prostatectomy.

Chapter 2, "Does Public Insurance Improve the Efficiency of Medical Care? Medicaid Expansions and Child Hospitalizations," addresses the relationship between health insurance availability and the nature and frequency of hospitalization. Together with co-author Jonathan Gruber, I find that the Medicaid expansions from 1983 to 1996 were associated with a 22% decline in "avoidable hospitalizations," hospitalizations that can potentially be averted by timely outpatient care. However, the increased insurance coverage had a larger, offsetting impact on other types of hospitalizations, yielding a 10% overall increase in child hospitalizations. The effects on intensity of care once in the hospital are ambiguous, but the data show that more children were treated in for-profit facilities, and fewer in public institutions as a result of the expansions in Medicaid.

Chapter 3, "Hospital Responses to Changes in Average Reimbursement Rates: An Assessment of a Natural Experiment," explores the effect of increased reimbursement to hospitals on billing practices (specifically, "upcoding") and intensity of care. Because the hospital industry is highly-regulated and predominantly not-for-profit, standard theories of firm behavior may not apply to hospitals, yielding ambiguous a priori predictions of hospital responses to reimbursement changes. My empirical analysis suggests that large increases in reimbursement for particular diagnoses were not met with increased spending on care for patients in those diagnoses. If upheld in future research, this finding has important implications for providers of health insurance, both public and private.

Accounting for one-third of health expenditures, and over 4 percent of GDP overall, the hospital sector is critical both to healthcare and to the economy at large. Understanding hospital behavior will require additional investigation of competitive practices as well as public interventions.

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Abstract

Recent health insurance initiatives have compelled hospitals to adopt traditional business behaviors, such as cost minimization and volume discounting. This paper investigates whether hospitals have also espoused more sophisticated business strategies, focusing on entry deterrence in surgical procedure markets. I investigate whether incumbent hospitals threatened by entry in profitable procedure markets take advantage of learning-by-doing in these markets to erect barriers to entry. I begin by presenting a model for an inpatient surgical procedure market with learning-by-doing. I then use this model to generate clear theoretical predictions regarding entry deterrence through learning-by-doing. Finally, I test these predictions on three different procedure markets: electrophysiological studies, liver transplants, and prostatectomy. In each of these case studies, I find only weak evidence consistent with entry deterrence through learning-by-doing.

1 Introduction

The hospital industry that has emerged after nearly two decades of cost-containment is both more efficient and more competitive. The survivors of the industry shakedown have adopted many traditional business practices, ranging from strict budgeting and heavy marketing to explicit collusion through affiliations with competitors. Due to the unique nature of the product supplied by hospitals, as well as the role that hospitals play in providing a public safety net for the uninsured, the welfare implications of these behaviors are substantial. This paper investigates the presence of one such business behavior: strategic investment for the purpose of entry deterrence.

The setting for this analysis is an inpatient surgical procedure market, such as the market for liver transplants. Research has shown that providers with more experience produce better outcomes, and as this research has disseminated, information about physician and hospital experience levels has become more accessible. The high degree of learning-by-doing in many of these markets raises the possibility that learning-by-doing may act as a barrier to entry, as noted by Ho (2000) in a recent study of the diffusion of coronary angioplasty. I investigate whether incumbent hospitals threatened by entry in a profitable procedure market increase their procedure volume to take advantage of this effect. Perhaps by creating a "center of excellence" in a given procedure market, hospitals can forestall new entrants, whose comparative lack of experience is unattractive to patients, physicians, and insurers alike.

The theory of strategic investment, in which an incumbent firm (the "first mover") adjusts its investment amount in period 1 because its choice affects play in period 2, originates in Stackelberg (1934) and is extended by Spence (1977,1979), Dixit (1979,1980), and others. Several of these authors, notably Spence (1984) and Fudenberg and Tirole (1983, 1986), note the possibility of using experience for strategic effect. The opportunity to squeeze or even eliminate competitors by moving quickly along a firm-specific learning curve is not lost on players in several key industries; for example, it is widely reported that airplane manufacturers price below cost for the first several hundred units of a new design, a strategy that often succeeds in deterring or severely handicapping the entry of competing aircraft (Newhouse 1982).

Although inpatient surgical procedures are a primary output of the hospital industry,

research on competition within surgical procedure markets – or even the concept of a surgical procedure market - is not well-developed. Several papers have explored the relationship between a hospital's decision to offer a particular service or surgery and the competitive environment in which it operates, but none has offered a structural interpretation of this relationship or provided a model of competitive play. In addition, the role of learning-by-doing in surgery, though well-documented, has only been linked anecdotally to market structure. This paper formalizes these relationships by explicitly modeling the demand and supply for surgical procedures, incorporating the role of learning-by-doing into the production function, and positing a differentiated-products game that governs play among market participants. I use this model to illustrate the incentives for strategic investment in learning-by-doing, focusing on incumbents' ability to deter entry through this channel.

Using data from the United Network for Organ Sharing for 1988-1998, and MEDPAR, the Medicare claims database, for 1984-1996, I test the predictions of this model on three different inpatient surgical procedure markets: electrophysiological studies, liver transplants, and prostatectomy. Each of these procedures experienced a positive demand and/or reimbursement shock during their respective study periods. By focusing on incumbent behavior following a positive shock to the profitability of a procedure, and comparing this behavior across markets with different levels of entry-deterrence incentives (i.e. markets where entry is effectively blockaded versus markets where several competing hospitals possess the prerequisites for entry into a given procedure market), I am able to detect limited evidence consistent with entry-deterring behavior in all three case studies. However, the findings are not robust to alternate specifications. Therefore, I can neither affirm nor reject the role of competitive motivations in treatment decisions.

The following section summarizes research on learning-by-doing in surgical procedures and strategic entry deterrence. Section 3 presents a simple dynamic model of competition in surgical procedure markets. Section 4 gives an overview of the case studies used to test the predictions of the model, including a summary of the empirical approach, a description of the data sources, and a preview of the results. Sections 5, 6, and 7 present the case studies for electrophysiological studies, liver transplants, and prostatectomy, respectively. A discussion of the findings and potential extensions follows in Section 8. Section 9 concludes.

2 Background

This study draws heavily from two distinct literatures summarized below: medical research on learning-by-doing in surgery, and theoretical and empirical economic research on entry deterrence models. I combine the results from these literatures, together with observations on hospital markets, to build a model of entry deterrence through learning-by-doing in surgical procedure markets. The empirical tests of this model contribute to the very sparse empirical industrial organization literature on entry deterrence, described in section 2.2. The empirical results also provide information on entry decisions by hospitals, a topic that has garnered substantial interest among healthcare researchers.

Concern over costly and unnecessary duplication of services peaked in the early 1980s, when hospitals were reimbursed on a generous cost-plus basis. At that time, most empirical research affirmed the presence of a "medical arms race" (MAR) among hospitals, in which hospitals raced to acquire the latest technologies in order to retain the best physicians. Contrary to standard competitive models, markets with the largest number of hospitals had the highest costs, and the MAR was seen as the culprit. A more recent study of California hospitals by Zwanziger and Melnick (1988) finds that the MAR prevailed in 1980-82, but in 1983-85, cost-containment initiatives changed the competitive dynamic and markets with more hospitals had lower cost growth than markets with fewer hospitals. Since the MAR, few theories of entry behavior have entered the mainstream literature. There are reduced-form analyses illustrating the relationship between new service introduction and patient demand or financial pressure (e.g. Hodgkin 1996), but few structural models of entry decisions.[1]

Yet an understanding of hospital decision-making is critical to formulating a range of policies, from antitrust initiatives to reimbursement schemes. Understanding the role of learning-by-doing in medical markets is also important, as growing evidence of this phenomenon has generated interest in regionalization of high-tech procedures; my model suggests that the market mechanism may take care of this problem to some degree. This paper investigates one aspect of the entry process, with the broader goals of contributing to a better understanding of hospital decision-making and of the sophistication of strategic interactions among hospitals.

[1] Exceptions include Chernew and Gowisankaran (2001), who model entry into bypass surgery as a function of expected patient flows, and Vogt (2000), who considers preemption motives for acquisition of magnetic resonance imaging (MRI) machines in duopoly hospital markets.

To set the stage for the model outlined in Section 3, I turn to the literature on learning-by-doing in surgery and entry deterrence.

2.1 Learning-by-Doing in Surgery

Since the late 1970s, medical researchers have published hundreds of articles investigating the relationship between surgical volume and patient outcomes. Although the magnitudes of the relationship differ across studies, procedures, and outcome measures, the resounding conclusion from this research is that, for many procedures, there are strong, positive correlations between procedure-specific hospital volumes and outcomes, and that these correlations are robust to detailed controls for patient risk factors, hospital characteristics, surgeon volume, and local sociodemographics.

Procedures with strong hospital volume/outcome relationships include coronary artery bypass surgery (CABG), cardiac catheterization, prostatectomy, total hip replacement, and resectioning of abdominal aortic aneurysms, to list only a few. Examples of procedures with weak or insignificant associations include cholecystectomy (gall bladder removal), inguinal hernia repair, and femur fraction reduction - all procedures that require less technical expertise to obtain successful outcomes.[2] Although this evidence is suggestive of learning-by-doing in surgery, there are a number of limitations of the medical literature that render such a conclusion premature. First, the outcome measures used in most studies - inpatient mortality, length of stay, and post-surgery complications - are extremely limited. Hospitals with low volumes are at greater risk for extremely high levels of these variables, simply due to statistical chance. Second, although the studies attempt to control for patient risk factors, the potential for omitted variables is clearly problematic. Third, these studies cannot distinguish between two alternate hypotheses for the volume/outcome phenomenon: the "practice makes perfect" or learning-by-doing hypothesis, and the "selective referral" hypothesis, which maintains that hospitals with good outcomes generate high volumes, rather than vice-versa.

The few studies that have attempted to separate these effects have found support for both. Simultaneous-equation estimates of the outcome-volume relation and the volume-

[2]The evidence on the relationship between surgeon volumes and outcomes is less conclusive, although there is consensus that a positive correlation is present for select procedures (e.g. carotid endarterectomy), and there is substantial evidence that very low-volume operators obtain extremely poor results across a range of surgical procedures (e.g. Hughes, Hunt and Luft 1987, Cebul et al. 1998).

outcome relation by Luft, Hunt, and Maerski (1987) reveal a significant, negative bilateral relationship for total hip replacement and hysterectomy. The "practice makes perfect" effect dominates for some acute conditions such as heart attack, where referral is less likely due to the emergency nature of the incident, as well as other conditions such as stomach and intestinal operations, which are usually managed by family physicians who may be insufficiently informed to guide patients to the best facilities.[3] The "selective referral" effect dominates for aneurysms, prostatectomy, and CABG, procedures which are likely to be preceded by specialty consultations. Patterns of hospital transfers also support the "selective referral" hypothesis for certain procedures, with high-volume facilities more likely to receive transfers for aneurysms, hemorrhages, and respiratory distress syndrome, among others. Mukamel and Mushlin (1998) find that facilities with superior CABG outcomes increased their market share relative to other facilities following the release of outcome data by the New York State Department of Health beginning in 1990. Finally, recent work by Ho (2000) extends the instrumental variables approach to hospital costs as well as industry learning-by-doing effects. Using data on angioplasties performed in California between 1984 and 1996, Ho finds evidence of hospital-specific as well as industry-wide learning-by-doing, both for outcomes and for costs.

This paper does not attempt to enter the debate described above, but the model outlined in section 3 borrows heavily from this literature. First, I use volume as an indicator of hospital quality, an assumption that reflects the "practice makes perfect" hypothesis. Second, I assume that patient demand responds to quality, the "selective referral" hypothesis. Finally, I require that hospitals are aware that volume begets volume, so they may consider strategies to increase their volume for competitive effect.

The prominence of procedure volume data in hospital marketing communications suggests that hospitals are indeed cognizant of this link. For example, the Cleveland Clinic website boasts, " [The] Cerebrovascular Center has one of the highest stroke-related patient volumes in North America. The Center treats over 2,000 cerebrovascular patients annually. High patient volumes provide our specialists with extensive experience, resulting in a team that

[3]Note that Hunt, Luft, and Maerski (1987) use data gathered in 1972 for the Professional Activities Study by the Commission on Professional and Hospital Activities (CPHA), as do many of the studies described in this section. Thus, hospital choice was far less restricted during the period explored in this body of literature than is the case today.

routinely treats common problems and manages rare disorders much more frequently than smaller centers." Organ transplant programs, cardiac surgery centers, and joint replacement services, among others, also emphasize procedure volumes in communications materials. In addition, medical associations, surgical accreditation boards, and HCFA provide procedure-specific volume guidelines for surgeons and/or hospitals. For example, Medicare will only cover liver transplants performed in HCFA-approved centers, and centers must perform at least 12 procedures per year to satisfy HCFA requirements.[4] The American College of Surgeons recommends at least 200 open-heart surgeries per hospital in order to "function efficiently" and attain quality goals. Finally, the growing body of volume/outcome research and concomitant calls for regionalization of specialized procedures suggest that hospitals are likely to be aware of the volume-outcome-volume link.

2.2 Strategic Entry Deterrence

The theoretical literature on entry deterrence is well-developed (see Wilson (1992) in *The Handbook of Game Theory* for a good review). Within this literature, works on strategic preemption, characterized by incumbents' efforts to retain market dominance through irreversible investments, are most pertinent to the topic at hand.[5] The critical insight from these models is that a sunk investment, be it in cost-cutting, capacity, advertising, or experience, credibly commits the incumbent to a particular course of action and therefore gives it an edge in strategic play. For example, an existing auto-assembly firm that builds a large new plant credibly commits to producing more vehicles in the event of entry (and perhaps in the absence of entry as well), thereby reducing the potential profits of an entrant and the likelihood of entry.

Spence (1984) demonstrates the role of the learning curve, or accumulated experience, in erecting barriers to entry. Specifying a unit cost function that decreases in accumulated experience, Spence illustrates the cost advantage that accrues to early entrants. Spence and subsequent authors (e.g. Fudenberg and Tirole 1986) emphasize the difference between

[4] Approval is site-specific, so a hospital cannot gain immediate approval by hiring a team of experienced surgeons.

[5] Wilson describes two additional broad categories of entry-deterrence models: signaling (or signal-jamming) models, in which incumbents convey (or block) information about their markets with the purpose of discouraging entry or promoting exit, and predation models, in which incumbents price aggressively to destroy the viability of an entrant.

simple precommitment ("open loop") equilibria, in which the first mover recognizes the future cost savings associated with increased output in the current period, and perfect ("closed loop") equilibria, in which the first mover also considers the effect of current output on competitors' actions. For example, in a perfect equilibrium, an incumbent that accumulates new experience in an industry characterized by Cournot competition not only recognizes that this experience will lower its costs and therefore increase its production in the future, but also that its competitors will reduce their future output levels in response to the volume increase. Recognition of the strategic value of production results in more production in early periods relative to the open-loop solution. This prediction is a critical component of the empirical strategy described in section 4, as I use volume spurts to measure the degree of strategic investment in procedure markets following a profitable industry shock.

The empirical literature on entry deterrence is rather sparse, with most studies documenting competitive responses to investment decisions rather than identifying strategic motives for the investments. Examples of such papers include Lieberman (1987), who finds that incumbents in concentrated chemical processing industries reduce investment in response to expansions by rivals, and Chevalier (1995), who finds that leveraged buyouts of supermarket chains are followed by softer product-market competition. Such studies suggest that capacity and capital structure are effective vehicles for strategic investment, but do not constitute prima facie evidence that such investment is taking place.

Two recent papers, Vogt (1999) and Ellison and Ellison (2000), construct specific tests for strategic preemption. Using data on adoption dates of magnetic resonance imaging (MRI) technology in duopoly hospital markets, Vogt finds evidence of preemption through early adoption by a rival. Due to the limited sample size (N=31) and extensive estimation assumptions, however, these results are perhaps best construed as tentative. Ellison and Ellison's test requires substantially fewer assumptions and reveals evidence of preemptive efforts by patent-holders in pharmaceutical markets; this is the empirical test I use, described in greater detail in section 4. Briefly, Ellison and Ellison study the advertising, product presentation, and pricing behavior of firms facing an immediate threat of generic entry due to patent expiration. Because the strategic incentive to deter entry is greatest in markets where entry is probable, as compared to markets where it is effectively blockaded (i.e. the drug has extremely small revenues) or extremely likely (e.g. Prozac), the authors look for investment

behavior that is nonmonotonic in entry probability. They find evidence supportive of entry deterrence: incumbents in medium-sized markets are more likely than incumbents in small or large markets to decrease advertising and increase the variety of product presentations immediately prior to patent expiration. Both behaviors reduce the expected profits of an entrant, and should increase monotonically with market potential if entry deterrence motives are absent.

In sum, the theoretical ideas tested in this paper are well-founded in the industrial organization literature, although the learning-by-doing model described in section 3 is specifically formulated to reflect the unique features of the hospital industry. This paper also contributes to the fledgling empirical literature on strategic entry deterrence, applying a recently-developed identification strategy to a vitally important industry.

3 A Model of Entry Deterrence Through Learning-by-Doing

3.1 Assumptions

In standard learning-by-doing models, firms that produce beyond the single-period optimal quantity acquire more experience at the expense of current profits, since the increased production drives market prices down. In hospital markets, however, supply and demand do not equilibrate contemporaneously via a price mechanism. The nation's largest insurer, Medicare, dictates a fixed price for each of roughly 500 Diagnosis Related Groups (DRGs), and most private insurers negotiate reimbursement amounts. A hospital seeking to expand current production in one of its product lines (say, cardiac surgery) must attract patients through other means: advertising, referral networks, amenities, and quality of care. Thus, price P is not considered a choice variable for hospitals in this model; hospitals may, however, adjust any of the other variables.[6]

A hospital can manipulate the other factors mentioned above, however, and I will aggregate these choices into a variable called *quality*, denoted by l. Quantity demanded for a given procedure in hospital i at time t is assumed to be an increasing function of hospital i's quality,

[6]Note that the model is tested on Medicare data, and since Medicare beneficiaries face the same out-of-pocket price at all hospitals, a hospital would not be able to increase volume by lowering price.

and a decreasing function of the quality of its competitors, denoted by $-i$:

$$Q_t^i = f(l_t^i, l_t^{-i}), \text{ where } \frac{\partial f_t^i}{\partial l_t^i} > 0 \text{ and } \frac{\partial f_t^i}{\partial l_t^{-i}} < 0$$

Although I have omitted procedure subscripts, all variables are at the procedure level, so that l and Q refer to quality and quantity for a particular procedure, respectively.

Learning-by-doing is incorporated in the production function for quality by including a term for accumulated experience. The other inputs into quality are jointly measured by the variable k, which can be loosely interpreted as current expenditure (on equipment, extra nurses, advertising, etc.). For simplicity, k is not durable and expires at the end of each period. The production function for quality can therefore be written

$$l_t^i = g(k_t^i, \overline{Q}_t^i), \text{ where } \overline{Q}_t^i = \Sigma_{j=1}^{t-1} Q_j^i, \frac{\partial g_t^i}{\partial k_t^i} > 0 \text{ and } \frac{\partial g_t^i}{\partial \overline{Q}_t^i} > 0$$

The second argument in g captures the "practice makes perfect" effect discussed in section 2, as procedure quality is assumed to increase in a hospital's experience with the procedure. The "selective referral effect" is reflected in the function for quantity demanded (f), in that a hospital acquires more patients if it offers a higher quality level. Thus, volume begets more volume. The role of k should not be understated, however, as it is the means by which a hospital produces quality upon entry, and also the only factor a hospital can adjust to rapidly increase quality, say in the face of an entry threat by a competitor.

The cost function for k can be written

$$C_t^i = r_t k_t^i$$

where r is the market-level factor price for k.

Last, I assume the entrant incurs a cost E upon entry, where E is stochastic and its cumulative distribution function $F(E)$ is known to all parties.[7]

[7] Were E not stochastic, the model would be deterministic: the k_1^M needed to deter entry would be known, and entry-deterring investment would either be successful or would not be undertaken at all. Such a model is unrealistic and not conducive to convincing empirical tests.

3.2 Model

I begin with a standard 3-period strategic investment model, summarized in the following diagram:

$t=1$	$t=2$	$t=3$
Incumbent monopolist chooses k_1^M (and therefore l_1^M) and earns $\pi_1^M(l_1^M(k_1^M), k_1^M)$	Potential entrant observes $Q_1^M(l_1^M(k_1^M))$ and the realization of E, and decides whether to enter	Monopoly payout $\pi_2^{*M}(l_2^{M^*}(k_1^M), k_2^{M^*})$ or duopoly payouts $\pi_2^{*D_M}(l_2^{D_M^*}(k_1^M), l_2^{D_E^*}(k_1^M), k_2^{D_M^*})$ and $\pi_2^{*D_E}(l_2^{D_M^*}(k_1^M), l_2^{D_E^*}(k_1^M), k_2^{D_E^*})$

where the superscript M refers to the monopolist when she is the sole supplier, and D_M and D_E to the former monopolist and the entrant, respectively, if entry occurs. The profit functions are assumed to be concave in the strategic investment k_1^M, and the payoffs in the event of entry result from a unique Nash equilibrium in the second-period game.

Assuming no discounting and rewriting the per-period profit functions solely in terms of the choice variable, k, the monopolist's maximization problem is simply

$$\begin{aligned}\max_{k_1^M, k_2^M, k_2^{D_M}} E(\pi) &= \pi_1^M(k_1^M) + F(\pi_2^{D_E}(k_1^M, k_2^{D_E}, k_2^{D_M})) \cdot \pi_2^{D_M}(k_1^M, k_2^{D_E}, k_2^{D_M}) + \\ &\quad (1 - F(\pi_2^{D_E}(k_1^M, k_2^{D_E}, k_2^{D_M}))) \cdot \pi_2^M(k_1^M, k_2^M)\end{aligned}$$

The solution for k_2 is straightforward: the incumbent simply picks the optimal amount given the competitive environment, spending $k_2^{M^*}$ or $k_2^{D_M^*}$. The first-order condition for k_1^M (after suppressing most of the arguments in the profit functions) is

$$\begin{aligned}-\frac{\partial \pi_1^M}{\partial k_1^M} &= F(\pi_2^{D_E^*}(k_1^{M^*})) \cdot \frac{\partial \pi_2^{D_M}}{\partial k_1^M}(k_1^{M^*}, k_2^{D_E^*}) + (1 - F(\pi_2^{D_E^*}(k_1^{M^*}))) \cdot \frac{\partial \pi_2^M}{\partial k_1^M}(k_1^{M^*}) + \\ &\quad F(\pi_2^{D_E^*}(k_1^{M^*})) \cdot \frac{\partial \pi_2^{D_M}}{\partial k_2^{D_E}}(k_1^{M^*}, k_2^{D_E^*}) \cdot \frac{dk_2^{D_E}}{dk_1^M}(k_1^{M^*}) + \\ &\quad (\pi_2^{D_M^*}(k_1^{M^*}, k_2^{D_E^*}) - \pi_2^{M^*}(k_1^{M^*})) \cdot f(\pi_2^{D_E^*}(k_1^{M^*})) \cdot \\ &\quad \left[\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M}(k_1^{M^*}) + \frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}}(k_1^{M^*}) \cdot \frac{dk_2^{D_M^*}}{dk_1^M}(k_1^{M^*})\right]\end{aligned}$$

The term on the left-hand-side measures the cost associated with investment beyond the single-period optimum; because this investment pays off in future periods as well as in the

current period, this term should be positive. The first two terms on the right-hand-side constitute the "open loop" or "non-strategic" first-order condition, in which the incumbent takes the entrant's behavior, including the probability of entry, as given. The third term is the "strategic entry accommodation" term, which incorporates the effect of the incumbent's investment decision in the first period on the entrant's choice of $k_2^{D_E}$. If it is greater (less) than zero, an incumbent that is accommodating entry in its market will overinvest (underinvest) in k_1^M relative to the open-loop optimum. My focus is on the fourth term, the "strategic entry deterrence" effect.

The magnitude of the entry deterrence effect increases in the difference between monopoly and duopoly profits in the second period, as well as the probability mass of E at $\pi_2^{D_E^*}$. Intuitively, this means that the incentive to deter entry is greatest when substantial profits are at stake, and when the entrant is likely to be "on the fence" in terms of its entry decision. Under these circumstances, a bit of overinvestment has a large payoff. Because $(\pi_2^{D_M^*} - \pi_2^{M^*})$ is always negative and $f(\pi_2^{D_E^*})$ is always positive, the sign of $\left[\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M} + \frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}} \cdot \frac{dk_2^{D_M^*}}{dk_1^M}\right]$ determines whether the incumbent will overinvest or underinvest in order to deter entry. Given the assumptions I have made about quality competition in the product market, the sign of this term will be negative and the entry deterrence effect will increase investment, as illustrated by the example given in Appendix B.

3.3 Generating Testable Predictions

Using first-order conditions to discern the presence of a strategic entry deterrence effect on hospital investment decisions would be prohibitively difficult; not only would the researcher need exact profit, demand, and quality functions, she would also need hospital investment data at the procedure-level. This section describes the two elements needed to transform the first-order condition into an empirically testable relationship.

First, I use a result derived in Ellison and Ellison (2000). The authors introduce a variable z into the profit and cost functions for the incumbent and the potential entrant, where z reflects market size or other characteristics associated with the probability of entry, and $\frac{d}{dz}\pi^{D_E^*}(k_1^M, k_2^{D_E}, k_2^{D_M}, z) > 0$. They illustrate that, under certain conditions, the incumbent's *strategic investment is monotone increasing in z in the absence of the entry-deterrence effect.* (This situation would prevail, for example, if the incumbent's investment were not revealed to

the entrant prior to the entry decision.)[8] The conditions under which this proposition holds are not demanding, and a more thorough discussion is presented in Appendix B. Intuitively, this result simply means that in the absence of entry-deterrence motivations, incumbents' investments will increase monotonically with market potential.

Having established monotonicity of investment in z when entry-deterrence objectives are absent, the authors then illustrate nonmonotonicity when entry-deterrence objectives are present. This follows intuitively from an examination of the entry-deterrence term, now

$$(\pi_2^{D_M^*}(k_1^{M^*}(z), k_2^{D_E^*}(z), z) - \pi_2^{M^*}(k_1^{M^*}(z), z)) \cdot f(\pi_2^{D_E^*}(k_1^{M^*}(z), z)) \cdot \left[\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M}(k_1^{M^*}(z), z) + \frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}}(k_1^{M^*}(z), z) \cdot \frac{dk_2^{D_M^*}}{dk_1^M}(k_1^{M^*}(z), z) \right].$$

$f(\pi_2^{D_E^*}(k_1^{M^*}(z), z))$, the probability density of entrants who are indifferent between entering and not entering the market, does not increase monotonically in market attractiveness. When the market is extremely attractive or unattractive, few entrants will be indifferent; $f(\pi_2^{D_E^*}(k_1^{M^*}(z), z))$ will be largest when z has an intermediate value. Because $f(\pi_2^{D_E^*}(k_1^{M^*}(z), z))$ is multiplied by the difference between duopoly and monopoly profits, the strategic entry deterrence effect can be rather large, generating an investment curve that is nonmonotonic in z. In the surgical procedure setting, the prediction is that investment in k_1^M will be greatest in markets where incumbents perceive entry to be possible, as compared to markets where entry is unlikely or likely. Figure 1 provides an illustration of such a pattern.

The second component needed to transform the incumbent's first-order condition into a testable relationship concerns the strategic investment variable k_1^M. Although k_1^M is unobservable, the end product of the investment, first-period procedure volume (Q_1^M), *can* be measured. Thus, changes in procedure volume, after controlling for covariates, proxy for changes in investment in quality. This result is a feature of the model sketched above; a profit-maximizing hospital would only spend money to boost quality if the quality improvement generated more business at the fixed price P. The result would be unaffected if quality itself had a positive weight in the hospital's objective function.

It is important to recognize that learning-by-doing is the strategic investment vehicle in

[8] The first-order condition used to obtain $k_1^{M^*}$ in this case *does* incorporate the strategic entry accommodation term described above.

this model, this apparent sleight of hand notwithstanding. An incumbent seeking to deter entry invests in quality in the first period because the resulting increase in first-period *volume* increases quality in the second period. The only way to "strategically invest in learning-by-doing" is to increase volume, and quality is simply the means of doing so in this model. As noted in the introduction to this section, incumbents in standard learning-by-doing models reduce price in order to sell more and "strategically invest in learning-by-doing." Here, quality, not price, is manipulated by the firms.

To summarize, the prediction of interest is that incumbents with strong motives to deter entry will spend money to boost their quality in period 1. This will increase the number of procedures they perform in period 1, raising their experience level in period 3, and depressing profits of a potential entrant in all subsequent periods. Because an increase in expenditure in period 1 translates directly into an increase in volume in period 1, I can use volume increases to study incumbents' investment behavior; I need not observe quality or expenditure. I will investigate whether incumbents in markets of intermediate attractiveness, where entry-deterring investment can have the greatest impact on the entry decision, exhibit stronger volume growth in the face of shocks that increase the likelihood of entry.

4 Overview of Case Studies: Empirical Strategy, Data, and Preview of Results

4.1 Empirical Strategy

To detect the presence of entry deterrence in surgical procedure markets, I conduct detailed case studies of surgical procedures that experienced positive profitability shocks. The shock generates a threat of new entry, and should therefore unleash entry-deterring investments if hospitals engage in this type of strategic behavior. In addition to a shock, the procedures I use must satisfy other key conditions dictated by the model: (1) a high degree of learning-by-doing; (2) a large fixed investment upon entry; (3) demand that is increasing in the quality of the procedure.[9] Data limitations further constrain the choice of procedures; although

[9]The existence of latent patient demand is critical to this model. For quality to have an impact on overall incumbent volumes, it must be feasible to "grow" the market. For example, the number of limb amputations in a market will not undergo large growth due to hospitals' quality enhancements, but the same is certainly not true of procedures such as prostatectomy or liver transplants.

nationwide data are available for organ transplants from 1988 onward, all other candidate procedures must be well-represented in the elderly population, as Medicare's inpatient database (MEDPAR) is the only source of national longitudinal data with a sufficiently large sample size for my purposes. I perform case studies on three procedures that satisfy these criteria reasonably well: electrophysiological studies (EPS), liver transplants, and prostatectomy.[10]

After selecting procedures, I identify the critical dates corresponding to t=1, t=2, and t=3, which designate the periods during which incumbents make investments (t=1 to t=2) and potential entrants make their entry decisions (t=2 to t=3). Next, I define geographic markets for the procedure and classify all incumbents and potential entrants (non-incumbent hospitals or some variant thereof) accordingly. I use the Metropolitan Statistical Area (MSA) boundaries employed by the Bureau of the Census between 1983 and 1990.[11] The choice of MSAs strikes a balance between the need to define markets large enough to capture the area in which hospitals compete for patients seeking these specialized procedures, but small enough to yield a sufficient sample size. Each market serves as an observation in my analysis.

Using market-level data on potential entrants, incumbents, and population, I then calculate a predicted probability of entry for each market. This number is an index of market attractiveness, i.e. the variable z. I use this index to divide markets into three groups reflecting the threat of entry: low, medium, and high. Finally, using my proxy for investment — the growth in incumbents' procedure volume between t=1 and t=2 — I look to see whether investment is nonmonotonic in z (that is, highest in the medium markets). Each component of this empirical strategy is described in greater detail within the case studies.

[10] To find these procedures, I identified surgical procedures that experienced a sudden technological change, or a large increase in Medicare reimbursement between 1984 and 1996, the period for which I have the MEDPAR data. I then reviewed medical literature and interviewed physicians to establish how well each procedure satisfies the technical criteria listed above. As a final screen, I used the Medicare and transplant datasets to identify providers for each candidate procedure, rejecting those procedures that were performed in only a small number of markets during the pre-shock period (e.g. extracorporeal photopheresis, a cancer treatment in which a patient's blood is passed through an external device and exposed to ultraviolet light) or on a small number of Medicare patients (e.g. bone marrow transplants).

[11] Providers not located in MSAs are dropped from the sample, but this restriction affects less than 5% and 2% of the prostatectomy and EPS providers, respectively, and none of the liver transplant centers. All sample restrictions and the number of affected hospitals are listed in the Data Appendix.

4.2 Data

For the EPS and prostatectomy cases, annual procedure totals for all hospitals are tabulated using the 20% sample of the 1984-1996 Medicare Provider Analysis and Review (MEDPAR) files. This comprehensive data source contains information on all hospitalizations of Medicare enrollees, including select patient demographics, diagnosis information, and hospital identification number. Up to 3 ICD-9-CM surgical procedure codes and surgery dates are listed for patients admitted between 1984 and 1987, and up to 10 such codes and matching dates are included for all records thereafter. The 20% sample comprises 2.1 to 2.8 million records per year.

Liver transplant volumes at the facility level are obtained from annual reports published by the United Network for Organ Sharing (UNOS), a nonprofit organization under contract to the Department of Health and Human Services to maintain the nation's transplant waiting list. The data, which is available from 1988 onward, constitutes a complete census of all liver transplants performed nationwide.

The three samples consist of all hospitals that performed the given procedure between t=1 and t=3, subject to a few restrictions detailed in the Data Appendix. For the EPS and prostatectomy cases, I add two sample restrictions to contend with the limitations of the MEDPAR data. First, because the files are a 20% sample, small hospitals are likelier to appear in the data as time goes on, and thus to be falsely labeled "new entrants." To minimize this problem, I drop all hospitals with fewer than 200 beds from each sample. Second, to avoid labeling a hospital as a "new entrant" simply because of a few coding errors, I drop any hospital that performed fewer than 3 procedures during the entire period for which I have the data, 1984-1996. The Data Appendix lists the number of hospitals dropped due to each restriction. Each hospital in the samples is then matched to a record from the *Annual Survey of Hospitals* by the American Hospital Association.[12] This survey provides detailed information on virtually all US hospitals, including service offerings and utilization statistics.

Table 1 contains a summary of the characteristics of the hospitals in each sample, along with similar data for all general hospitals in the US. The table reveals that liver transplant providers are the most sophisticated group by any measure, followed by EPS providers

[12]For each sample, I match AHA records from the survey year corrresponding to t=1. For hospitals that do not match in this year, I first attempt to match data using AHA files after t=1, and failing that, before t=1.

and then prostatectomy centers. Hospitals in all three samples are significantly larger than average, less likely to be for-profit or government-owned, and more likely to provide sophisticated services such as open heart surgery and therapeutic radiation. Although the hospital-level data is not directly used in the first or second-stage analyses, it provides a profile of likely entrants that is utilized to define the potential entrant measures.

The hospital data is aggregated to the MSA level, yielding 200, 63, and 311 MSAs with at least one provider between t=1 and t=3 for EPS, liver transplants, and prostatectomy, respectively. Because I am investigating incumbent responses to entry threats, I must drop MSAs that do not have at least one provider at t=1.[13] The resulting sample sizes are 155, 37, and 273. Descriptive statistics for these samples are provided in Table 2.

In addition to the mean number of incumbents and entrants per MSA, Table 2 also lists the number of entrants between t=1 and t=2. The data reveal that roughly 30% of the entrants in each case study enter during the incumbents' investment period, when entrants are theoretically observing incumbents' moves. This empirical reality and the problems it presents are addressed within the individual case studies. Total incumbent volumes are reported for each year between 1988 and 1996; although I present the sample totals for the EPS and prostatectomy cases, these figures should be multiplied by five to get an accurate estimate of real volumes. Volume per MSA increases markedly over time for all three samples, although the prostatectomy volumes peak in 1992 and decrease thereafter. Incumbent volume growth from t=1 to t=2, the investment measure, averages 40%, 70%, and 11% among EPS, liver transplant, and prostatectomy incumbents, respectively. The potential entrant variables and incumbent controls are described in the case studies.

4.3 Preview of Results

With small sample sizes, examining raw data is helpful in evaluating the validity of a model. Table 3 summarizes incumbents' investment behavior using raw (that is, unadjusted) volume growth rates by market type (low, medium, and high ex ante probability of entry). For each case study, I present the 4 market classification schemes that are used in the regressions discussed below. The first two schemes classify markets using predicted entry probabilities

[13] I also drop one large outlier market for liver transplants: Pittsburgh. The University of Pittsburgh pioneered liver transplantation, performing 441 procedures in 1989 – more than 13 times the amount for the average facility, and nearly 2.5 times more than the second-largest program, at UCLA.

from a basic entry model without extensive controls for incumbent characteristics. The second two schemes use probabilities from an expanded model. Within these two categories, I use two different sets of probability cutoffs to define the low, medium, and high groups. By considering various classification schemes, I test the sensitivity of the investment pattern to this choice. All of the definitions are described in more detail within each of the case studies.

Table 3 reveals nonmonotonic investment patterns for all procedures when the basic entry equation is used to predict entry probabilities, but no consistent pattern when markets are classified using richer entry models. The large standard errors on the group means indicate that the statistical significance of any differences across market types will be difficult to establish. Table 3 gives an accurate preview of the regression results that follow: nonmonotonic investment patterns are present primarily in models with few controls, and are statistically indistinguishable from monotonic investment patterns.

The individual case studies that follow describe the background, methodology, and regression results for each procedure.

5 Electrophysiological Studies (EPS)

5.1 Background

Introduced in the early 1980s, electrophysiological studies (EPS) are highly-specialized invasive procedures to identify and possibly treat cardiac arrhythmias. The heart is stimulated at various rates and cadences, and electrode catheters placed within veins or arteries record the responses. Therapeutic ablation, in which tissue is destroyed using high-frequency currents, may also be performed.[14] Although the procedure is extremely costly (hospitals reported expenses of $5,000 to $21,000 in 1988), EPS did not affect DRG assignment until FY90. Patients undergoing EPS were frequently placed in DRGs 138 and 139 for cardiac arrhythmias, with 1988 reimbursements of roughly $1800 and $2700, respectively. In September 1988, HCFA announced it was considering a policy change and established a new procedure code to facilitate the collection of more data. In September 1989, EPS was designated a "non-OR procedure," placing recipients in higher-paying surgical DRGs. FY89 reimbursements

[14] *The Miller-Keane Medical Dictionary; Manual of Cardiovascular Medicine (2000).*

for these DRGs (104, 106, 108, and 112) ranged from $6,600 to $25,700.[15] Figure 3 presents annual data on the number of Medicare patients undergoing EPS between 1984 and 1996.

Because HCFA's first announcement occurred toward the end of 1988, I select 1988 as t=1. Since the lead time for entry is not particularly long, 1989 is t=2. I allow three years for entrants to respond to the new reimbursement policy, setting t=3 at 1992.

EPS satisfies all of the modeling assumptions detailed in section 3.1. It is performed in a specially-equipped cardiac catheterization lab or radiology suite, indicating a large fixed entry cost (E). The *Manual of Cardiovascular Medicine* stresses the importance of a highly experienced operator in obtaining a successful outcome, affirming the presence of a high degree of learning-by-doing. Residents must complete 8 years of training before being permitted to *assist* in an EPS. Whether patients themselves are able to respond to improved quality for this procedure is not known, but an EPS patient is typically referred by a specialist, who should be aware of quality differentials among area hospitals. Finally, tabulations using California's census of hospital discharges, provided by the state's Office of Statewide Health Planning and Development, indicate that roughly half of EPS procedures are performed on Medicare beneficiaries. Because I use Medicare data to estimate hospital volumes, it is critical that Medicare patients constitute a significant portion of these totals.

5.2 First Stage: Predicting Entry Probabilities, EPS Case

As described in section 4.2, the hospital data from the MEDPAR and AHA files is aggregated to the MSA level for this analysis. Of the 155 MSAs with at least one EPS provider at t=1, 84 had one or more entrants by t=3. To calculate an *ex ante* probability of entry for each MSA, I follow the methodology employed by Ellison and Ellison (2000). Using actual entry experience, I create a dummy for entry between t=1 and t=3 at the MSA level. I then run a probit regression of entry on MSA characteristics, including number of incumbents/population (called "access to care") and mean years of incumbent experience, both of which should act as deterrents to entry, and a measure for the number of potential entrants (this is the regressor that is omitted in the second stage).[16] I estimate this equation

[15] Estimates calculated by multiplying DRG weights by the standard hospital amount for large urban hospitals (Sources: 53 FR 38476 and 54 FR 19636).

[16] Years of experience is measured as the number of years an incumbent has been in the sample as of t=1. Other covariates I considered include initial market penetration rate (volume at t=1/population), initial

with and without controls for incumbent hospital characteristics and low initial volume:

$$\begin{aligned}\Pr(\text{entry})_i = {} & \alpha + \beta_1[\text{number of potential entrants}]_i + \beta_2[\text{number of potential entrants}^2]_i + \\ & \beta_3(\text{access to care})_i + \beta_4(\text{incumbent experience})_i + \\ & [\beta_5(\text{incumbent characteristics})_i + \beta_6(\text{initial volume control})_i] + \varepsilon_i\end{aligned}$$

where i indexes MSAs.

Potential entrants are hospitals that match incumbents' profiles, as given in Table 1, and/or possess certain facilities that are prerequisites to establishing the new service. I considered several definitions for this measure, selecting the one with the most predictive power: the number of (non-incumbent) hospitals in each MSA with cardiac catheterization (cath) labs and open-heart surgery centers. A cath lab is a prerequisite to establishing EPS, while open heart surgery is a complement to EPS. Summary statistics for all of the market data and potential entrant variables are listed in Table 2.

The incumbent characteristics (summarized at the market level) are: the fraction of incumbents in each ownership category (for-profit and non-profit; government is the omitted group), the fraction that are teaching hospitals, the fraction with cath labs and open heart surgery programs, the mean number of annual surgical operations, and the mean number of beds. The volume control is an indicator variable for markets with very low initial volume levels; this is relevant primarily in the second-stage, as explained in the next section. Because these variables should be correlated both with the strength of existing providers (an entry deterrent) as well as with general market potential (an entry incentive), there are no a priori predictions regarding the signs of their coefficients.

Table 4 gives the coefficients from the entry equations. The pseudo-R^2 values for these first-stage regressions are high (.39 and .45), with both the number of potential entrants and its square attaining significance at the $p < .01$ level, and access to care and experience entering with p-values below .05 and .10, respectively. The signs on all of these variables conform to expectations. The results show that the probability of entry increases with the number of entrants, at a slightly decreasing rate. Increasing incumbents' average years of experience by .78, or 25% of the mean value, reduces the probability of any entry by .06-.07.

market volume, and number of incumbents and population as separate terms. While the ratio of incumbents to population is a better predictor of entry than its component variables, the volume measures did not enter significantly into any of the first-stage regressions, so they are omitted here.

The adequacy of market coverage also matters to entrants; an increase of .1 incumbents per 100,000 population (again representing a 25% increase relative to the overall mean) reduces entry probability by .05.

Using the coefficients in Table 4, I calculate two predictions of the probability of entry for each MSA — one using the base model in column 1, and one using the model with controls (column 2). This probability is the explanatory variable of interest in the second stage. I use it to define a categorical variable that classifies markets as facing "low," "medium" or "high" entry probabilities. To test the sensitivity of the results to the cutoffs used to classify markets, I present findings for two alternate versions. These definitions and the number of markets assigned to each category are given in Table 5.

One concern with this approach is the possibility that predicted entry probability, which is intended to measure the *ex ante* threat of entry, is endogenously determined. If hospitals that faced a medium ex ante threat of entry succeeded in increasing volume and deterring entrants, this methodology could bias their predicted entry probability downward, raising the growth rate observed in the so-called "low" markets. Although this problem creates a bias against my hypothesis, I address it in two ways. First, I restrict the potential entrant variable to be continuous. A continuous entrant variable ensures that the estimated relationship between the latent index of entry probability and the number of entrants is monotonic, which more accurately captures the ex ante threat of entry. Second, I present results using two crude, but unbiased measures of market potential. The first categorizes markets into low, medium, and high entry-probability groups by whether the number of potential entrants for each market falls in the bottom, middle, or top third of the overall distribution for the number of potential entrants. The second measure groups the markets in the same way, but using thirds of the population distribution. Although this method cannot capture multiple determinants of entry or produce a continuous probability index, it provides a check on the results.

5.3 Second Stage: Exploring Investment Behavior, EPS Case

To test for the presence of a nonmonotonic relationship between investment and entry probability, I estimate two basic specifications. The first uses discrete variables to capture the likelihood of entry, while the second uses the continuous probability index as an independent variable:

$$(1)\ (\text{incumbent volume growth, t=1 to t=2})_i = \alpha + \beta_1[\Pr(\text{entry=medium})]_i +$$
$$\beta_2[\Pr(\text{entry=high})]_i + \beta_3(\text{access to care})_i + \beta_4(\text{incumbent experience})_i +$$
$$[\beta_5(\text{incumbent characteristics})_i + \beta_6(\text{initial volume control})_i] + \varepsilon_i$$
$$(2)\ (\text{incumbent volume growth, t=1 to t=2})_i = \alpha + \beta_1[\Pr(\text{entry})]_i +$$
$$\beta_2[\Pr(\text{entry})^2]_i + \beta_3(\text{access to care})_i + \beta_4(\text{incumbent experience})_i +$$
$$[\beta_5(\text{incumbent characteristics})_i + \beta_6(\text{initial volume control})_i] + \varepsilon_i$$

A finding of $\beta_1 > \beta_2$ in specification (1) constitutes conclusive evidence of entry deterrence; as Figure 1 illustrates, such a result requires an extremely strong entry deterrence effect. If the underlying monotonic relationship between volume growth and entry probability is steep or convex, medium markets will not exhibit significantly higher growth than high markets, even in the presence of entry deterring behavior. Because the omitted category is low entry probability, both $\beta_1$and β_2 should be greater than zero. In specification (2), $\beta_1 > 0$ and $\beta_2 < 0$ would indicate a downward-opening parabola, a pattern that is suggestive of entry deterrence provided that the maximum of the parabola occurs at a point sufficiently below $\widehat{pr}$=1.

The prediction for the sign of β_3 is ambiguous; while better access to care may enable faster volume growth, it may also indicate market saturation or maturity and therefore lower growth. Because experience increases procedure quality, β_4 should be positive. The remainder of the controls, listed in the preceding section, represent other possible determinants of market growth rates. With the exception of the ownership variables, for which there is no a priori hypothesis, the coefficients on all of the hospital controls are expected to be positive. Teaching status, the strength of a hospital's cardiology service, and hospital size should be positively related to the volume of patients for this sophisticated cardiac procedure. Because the data source is a 20% sample of Medicare patients only, some of the initial volume levels are extremely low, generating large percentage increases between t=1 and t=2 simply because of the tiny base amount.[17] To minimize the bias from this phenomenon, I include a dummy for volume of 5 or fewer procedures in t=1. The coefficient on this variable should be large and positive.

[17]Indeed, there are no procedures recorded for 28 of the MSAs with incumbents in 1988. These hospitals are in the sample as incumbents because there are records indicating that they performed procedures before *and* after 1988. Eliminating all hospitals with zero recorded procedures in any year is infeasible, as this characterizes 55% of the sample.

The unadjusted growth rates by market type, presented earlier in Table 3, presage the regression results. A nonmonotonic investment pattern is present only when the control variables are excluded from the first and second-stage regressions, and is much stronger for definition 1. The first panel in table 6 reports the key coefficients from four regressions based on specification 1. Columns 1 and 2 present results using definition 1 to classify markets, while 3 and 4 use definition 2. Columns 1 and 3 do not include the hospital or volume controls, which are added to the regressions presented in columns 2 and 4. The nonmonotonic pattern is pronounced in column 1, extremely weak in column 3, and absent in columns 2 and 4. In addition, even in column 1, where growth in the medium markets is significantly higher than growth in the low markets, the hypothesis that growth in the medium and high markets are the same cannot be rejected. Therefore, the findings from specification 1 offer little evidence of entry deterrence.

The results from specification 2, displayed in the second panel of table 6, are suggestive of entry deterrence even when all controls are included, but none of the coefficients on the probability of entry terms is significant. The parabolas estimated with this specification peak around $\widehat{pr}$=.68, indicating that both probability ranges for the medium markets in specification 1 are a bit low for this case study. Figure 5 graphs actual market growth rates against predicted entry probabilities, after eliminating the component of the growth rate that is predicted by access to care, incumbent experience, and the constant term. I use the coefficients on these terms from the regression in column 1 to calculate this component; the coefficients on the probability of entry and its square generate the parabola that is superimposed on the graph. While markets with intermediate entry probabilities exhibit the largest growth rates, the data are noisy, and it is difficult to (visually or statistically) rule out a monotonically increasing pattern.

The positive coefficient on access to care indicates that, ceteris paribus, markets with more providers per capita display stronger volume growth. One mechanism for this phenomenon is physician referrals. If EPS is available at more local hospitals, non-academic cardiologists may be more informed about it and therefore more likely to refer patients to an EPS specialist. As expected, hospitals with more experience grow faster as well, although this effect is never statistically significant.

The controls explain little of the variation in the EPS growth rates; none is individually

significant, nor are the hospital controls jointly significant as a group. The coefficient on the fraction of incumbents that are government-owned is large, negative, and nearly significant in all specifications, however, suggesting that public hospitals did not pursue this new market as aggressively as their not-for-profit or for-profit counterparts. The low volume control has a large, positive coefficient in all specifications, as expected.

Panel 3 gives results using the crude market definitions described in section 5.2. When the number of potential entrants defines market type, there is a nonmonotonic investment pattern that is robust to the inclusion of the hospital and volume controls. A monotonically increasing trend is evident when population is the sole classification criterion. This trend does not rule out entry deterrence, however, because market growth should clearly increase with population, regardless of entry threats. Although both results are consistent with entry deterrence in EPS markets, because the equality of the medium and high-market coefficients cannot be rejected in either case, neither result offers conclusive evidence of this strategic behavior.

The potential for early entry to affect observed incumbent investment patterns is substantial. Because virtually all of the markets that experience early entry are (appropriately) classified in the medium or high probability of entry groups, incumbent volume growth between t=1 and t=2 will be lower in these groups if any business-stealing takes place following entry. This effect will be strongest in the high markets, raising the potential for a spurious nonmonotonic investment pattern. To address this concern, I reestimate all of the equations in Table 6, replacing incumbent volume growth between 1988 and 1989 with *market* volume growth. This conservative approach attributes all volume of early entrants to incumbents, and creates a bias against detecting a nonmonotonic pattern. Although this modification reduces the coefficient on the medium market dummy in every specification, this dummy remains statistically significant in the same specifications as in Table 6, with the exception of panel 3, column 3 (which, importantly, did not display a nonmonotonic pattern even before the variable change).

To summarize, while there is some evidence that 1988-89 incumbent volume growth was strongest in markets facing an intermediate threat of new entry, this finding is not robust to the inclusion of multiple incumbent control variables. Furthermore, the differences between the medium and high-type markets are not statistically significant.

6 Liver Transplants

6.1 Background

Although the first liver transplant was performed in 1963, the procedure only became viable in 1983, following the introduction of cyclosporine, a powerful immunosuppressant. By 1985, more than 600 procedures were performed annually in the United States, and by 1998, this figure had increased seven-fold. Figure 3 presents national annual totals for liver transplants between 1985 and 1998, as reported by UNOS. An estimate of transplants in Medicare beneficiaries, tabulated using the MEDPAR 20% file, is graphed along the second y-axis.

HCFA announced its intention to cover the procedure in March 1990, for seven specified conditions (55 FR 8545). Although the new coverage was not officially approved until April 1991, it was made retroactive to March 1990, so 1989 is t=1 and 1991 is t=2.[18] All hospitals that performed at least one liver transplant in 1989 are classified as incumbents, while those entering after 1989 are considered new entrants. Incumbents' investments during 1990 and 1991 constitute k_1^M. Due to the long lag time involved in setting up a new facility and obtaining approval from state and federal regulators, I allow a five-year period for potential entrants to respond to the new coverage decision, designating 1996 as t=3.

The liver transplant case also satisfies the prerequisites dictated by the model. Entry costs, which include the construction of patient rooms with expensive air exchange systems, the purchase of specialized equipment, and arduous approval processes, are substantial.[19] Learning-by-doing is enormous, as evidenced by the relationship between survival rates and patient volume, as well as HCFA's requirement that facilities perform a minimum of 12 transplants per year *in adults with one of the seven covered conditions* for two years running to attain (and maintain) certification. Because detailed survival data at the facility level are widely publicized by UNOS and its members, increased program quality is likely to bring in additional patients. (The exponential growth in the number of patients on the transplant waiting list attests to the demand response to improved survival rates.) Finally, although Medicare beneficiaries account for a small (but growing) share of total liver transplants (~2%

[18] Medicare coverage of liver transplants in children under 18, for certain medical conditions, has been in place since February 1984.

[19] Although many facilities are common to all organ transplants, so that hospitals with an existing transplant program face lower entry costs than hospitals without such a program, there are organ-specific costs.

in 1988 but ~12% by 1996), Medicare coverage decisions typically influence coverage decisions by state Medicaid programs as well as private insurers, so the impact is greater than the Medicare patient totals suggest. In addition, HCFA certification as a Medicare transplant provider appears to be important to the success and credibility of transplant programs. Other insurers restrict coverage to transplants performed in these centers, and HCFA approval is often advertised on centers' websites.[20] Importantly, I use a national *census* of transplant data for my analysis, so the only Medicare-related requirement is that HCFA's coverage decision created an incentive for entry.

6.2 First Stage: Predicting Entry Probabilities, Liver Transplant Case

Of the 37 MSAs with a liver transplant facility in 1989, 11 gained at least one additional center by 1996. The Houston and Los Angeles MSAs each gained two new programs, and New Orleans and New York City each gained *three*. To generate ex ante predictions of the entry probability for each MSA, I use the methodology described in the EPS case study (section 5.2). However, the potential entrant measures reflect the profiles for liver transplant providers. Among the variants I considered, the measure with the strongest predictive power (bolded in Table 2) is the number of teaching hospitals that performed other organ transplants in t=1. In addition, incumbents' experience is not available because the provider-level data begin in 1988, just one year prior to t=1. All of the control variables are identical to those used in the EPS specifications, but the fraction of incumbents with cath labs and open heart surgery programs is replaced with the fraction of incumbents with cancer programs, a more relevant service for a liver transplant center.

None of the regressors in the probit entry equations presented in Table 7 is individually significant, but jointly they predict entry outcomes fairly well; the pseudo R^2 is .25 without the incumbent controls, and .41 when they are all included. The likelihood of entry increases exponentially with the number of non-incumbent teaching and transplant hospitals, and decreases with the level of existing market coverage.

Table 8 gives the boundaries for two alternate market definitions, which are applied to

[20] Only 56 of 90 non-military, adult programs had earned this distinction by 1996. (*Sources*: UNOS; List of Medicare-Approved Liver Transplant Centers, HCFA Division of Integrated Delivery Systems, www.hcfa.gov/medicare/livrlist.htm). Examples of centers advertising approval include the University of Pennsylvania Health System (www.med.upenn.edu/health/hi_files/transplant/about_penn_trans_ctr.html), and Vanderbilt Medical Center (http://www.mc. vanderbilt.edu/transplant/liver.htm).

predicted entry probabilities from both entry models. Very few markets have a high predicted probability of entry; using the basic model without controls, only 3 of the 37 markets have a $\widehat{pr} > .75$, and only 5 have a $\widehat{pr} > .5$. For this reason, the upper boundary for medium markets is set at .4 for the liver transplant case, and the lower boundaries are adjusted downward.

6.3 Second Stage: Exploring Investment Behavior, Liver Transplant Case

To analyze how investment behavior changes with the threat of entry, I pursue the same approach described in the EPS case, estimating two main specifications for volume growth by incumbents between t=1 and t=2. The independent variables of interest in specification (1) are the dummies for Pr(entry)=medium and Pr(entry)=high, and in Specification (2) the continuous probability terms, Pr(entry) and Pr(entry)^2. Again, I estimate these specifications with and without controls for incumbent characteristics and initial MSA volume; the regressions with (without) controls use the probability predictions from the corresponding first-stage regression with (without) controls.

Table 9, organized in the same way as Table 6, shows that there is a strong nonmonotonic growth pattern in the specifications without controls. Although this pattern is robust to alternate market definitions, it is not robust to inclusion of the control variables. In addition, the coefficients are not estimated with sufficient precision to reject equality of the growth rates in the medium and high-type markets. The graph of adjusted incumbent growth rates against entry probabilities, along with the parabola fitted to these growth rates by the regression in column 1, panel 2, is given in Figure 6. The scatterplot shows a large cluster of observations with extremely low entry probabilities, and a small group of markets with fairly high entry probabilities. Markets with intermediate entry probabilities exhibit the strongest growth rates, but again, the data are noisy.

As in the EPS case, the large, positive, and frequently significant coefficient on access to care indicates that a greater availability of this service is associated with faster volume growth. The explanatory power of the hospital controls is largest in this case; although few of the variables are individually significant, they are always significant as a group. In contrast to the EPS case, not-for-profit programs grow more slowly than government programs. As expected, MSAs with higher initial volumes have lower average growth rates.

The results using only potential entrants or population to categorize markets are mixed.

The coefficients in panel 3 of table 9 indicate the reverse (i.e. decreasing and then increasing) nonmonotonic investment pattern when potential entrants serve as the sole classification criterion, although these coefficients are not statistically significant. When thirds of the population distribution are used to classify markets, there is a very strong nonmonotonic investment pattern (increasing and then decreasing) that is robust to inclusion of the control variables. This pattern is remarkable because the underlying positive relationship between volume growth and population should be quite strong, as in the EPS case; the nonmonotonic pattern identified in these regressions suggests very strong efforts to deter entry.

To investigate the effect of early entry on these results, I reestimate all of the equations in Table 9 using market volume growth between t=1 and t=2 as the dependent variable. None of the results is substantively affected by this change, suggesting that early entry is unlikely to be driving these findings.

To conclude, there is some evidence that is consistent with entry deterrence through learning-by-doing in transplantation. However, the number of observations is too small to reject a hypothesis of parity between medium and high-type markets in the regressions where a nonmonotonic investment pattern is identified, and there are some specifications in which such a pattern is absent altogether.

7 Prostatectomy

7.1 Background

Prostatectomy, or removal of the prostate gland, has long been a standard treatment for cancer confined to the prostate. Until the mid-1980s, prostate cancer was only detectable through a digital rectal exam, followed by biopsy. In 1986, the FDA approved the prostate-specific antigen (PSA) test, a simple blood test to monitor the functioning of the prostate. Although the PSA test was only approved for use in patients already diagnosed with prostate cancer, physicians nationwide used it as a screening device, more than doubling the rate of detected cancers between 1986 and 1992.[21] Because more of the tumors identified with the PSA test were detected when the cancer was still localized, the number of prostatectomies

[21] According to the National Cancer Institute, between 1986 and 1992 the incidence of (detected) prostate cancer rose from 86 to 179 per 100,000 white men, and 124 to 241 per 100,000 black men. The first test sanctioned to detect cancer in asymptomatic patients was approved by the FDA in 1994.

increased even more dramatically, from roughly 12 per 100,000 men in 1986 to a peak of 55 per 100,000 men in 1992. Data from the 20% MEDPAR files, graphed in Figure 4, show that the number of prostatectomies performed on Medicare beneficiaries increased *eightfold* during this period. The decline between 1992 and 1996 is not due to a decline in the popularity of prostatectomy as a treatment, but rather to a decline in detected cancers. One hypothesis for this decline is that a large portion of the stock of prostate cancer was identified in the years immediately following the introduction of the PSA test, and so a greater share of the cases after the initial shock were new cancers.

Because the effect of the PSA test increased gradually over time, identifying the critical dates for this procedure is difficult. Incumbent providers did not face a heightened threat of entry until procedure volumes began to accelerate. For this reason, I set t=1 at 1988, immediately following the first noticeable volume spurt. To minimize the number of markets with entrants between t=1 and t=2, t=2 is one year later, 1989. As with EPS, I allow three years for entrants to respond to the rising demand for the procedure, designating 1992 as t=3.

While the shock to prostatectomy is the largest of the three shocks I study, on the remaining procedure selection criteria, prostatectomy does not perform as well. Entry costs may be high if a new provider invests in an entire cancer program when entering the prostatectomy market, but they may be low because the procedure can be performed in a standard operating room. The potential for learning-by-doing is great, but as yet unconfirmed. Unless the operator is experienced with nerve-sparing surgical techniques, incontinence and impotence are likely side effects of the surgery; whether "practice makes perfect," however, is unclear. Due to the serious side effects of this surgery, the link between patient demand and quality ("the selective referral effect"), however, *is* likely to be strong. Finally, Medicare beneficiaries are a good sample population for prostatectomy, as more than 75% of prostate tumors occur in men aged 65 and higher (Henkel 1994).

7.2 First Stage: Predicting Entry Probabilities, Prostatectomy Case

Despite the high number of prostatectomy incumbents in 1988 (888 hospitals, with an average of 3.26 providers per market), between 1988 and 1992, new providers entered in 39 percent of the 273 MSAs in the sample. Multiple entry is extremely common, with an average of 2.7 entrants per market with entry. The number of non-incumbent area hospitals that offer

radioactive implants, a sophisticated cancer therapy, proves an excellent predictor of any entry in the first-stage probit regressions, presented in Table 10. Increasing the number of such hospitals from 1 (the sample mean) to 2 raises the probability of entry by .26-.27. As in the other cases, incumbent experience and market coverage both act as significant deterrents to entry. An additional year of experience reduces the likelihood of entry by nearly .06, while a 25% increase over the mean access to care ratio reduces the likelihood of entry by .11. The hospital and volume control variables, which have only slight effects on the estimated coefficients, are the same as those used in the liver transplant case, but the fraction of incumbents that offer radiation therapies replaces the fraction of incumbents with cancer programs.

The market definition data in Table 11 shows a large number of observations with extremely low predicted entry probabilities, although the distribution of probabilities is not skewed as strongly to the left as for the liver transplant MSAs. Using probability predictions from the basic entry equation without controls, 52 of the MSAs have predicted entry probabilities greater than .75, the upper cutoff for medium markets. When controls are included in the entry equation, this total rises to 57 (of course, the first group is not necessarily a subset of the latter group).

7.3 Second Stage: Exploring Investment Behavior, Prostatectomy Case

As with the other case studies, the unadjusted growth rates by market type, displayed in Table 3, exhibit a pronounced nonmonotonicity in entry probability when the basic entry model is used to categorize markets. Average growth rates are much smaller in this case study, however, due to the choices for t=1 and t=2. Focusing again on the top section of Table 3, markets in the medium category grew at a brisk pace of 29 to 40% between 1988 and 1989, but the low-type markets barely grew at all, and the high-type markets saw *declines* in volume. The regression results, presented in Table 12, corroborate this pattern. While the coefficient on the medium market dummy is positive in 7 of the 8 models using specification (1), the coefficient on the high-market dummy is frequently negative.

The polynomial specification in panel 3 works well for the prostatectomy data when controls are not included. This specification indicates that maximum growth occurs around $\widehat{pr} = .56$. The results from this regression are used to adjust the growth rates and to calibrate

the parabolic trendline displayed in Figure 7. As with the other cases, the data are extremely noisy, explaining the overlapping confidence intervals for growth in all market types.

In virtually all of the specifications, incumbents' years of experience is positively and significantly associated with volume growth. However, access to care has a negative (though rarely significant) coefficient, suggesting that in this case study, wider availability of prostatectomy services may be a sign of market saturation. The hospital and volume controls explain little of the variation in incumbent growth rates. Contrary to expectations, the fraction of incumbents with teaching programs and the fraction of incumbents offering radiation therapies enter negatively and significantly in some of the specifications in which they are included. The signs of these coefficients are somewhat surprising, but may simply be due to the multiplicity of controls in the model.

Categorizing markets solely by the number of non-incumbent area hospitals with radioactive implant capabilities, the definition used for potential entrants, works about as well as the probability index itself, although it is robust to the inclusion of the control variables. Using population to group markets, however, produces larger and more precisely estimated coefficients on the medium-market dummy. Again, growth rates that are nonmonotonic in population suggest rather strong entry deterrence effects. Of course, it is possible that there are other sources of this nonmonotonicity, and it would be helpful to confirm a monotonic relationship between growth rates and population in a series of unrelated procedures that are not characterized by learning-by-doing.

Finally, although entry between t=1 and t=2 does occur disproportionately in markets with high predicted entry probabilities, attributing early entrants' volume to incumbents does not affect the results presented in Table 12.

The prostatectomy results are similar to those in the other case studies, notwithstanding the concerns over low entry costs and undocumented learning-by-doing. Although the point estimates for virtually all of the specifications indicate a nonmonotonic investment pattern, the large standard errors render the differences among even the low and medium markets statistically insignificant in most cases. A larger dataset is necessary to arrive at firm conclusions on entry deterrence in prostatectomy markets.

8 Discussion

The results across all three case studies are remarkably consistent. When entry probabilities are estimated using a limited number of incumbent control variables, markets with intermediate probabilities exhibit stronger growth rates than markets with low or high probabilities. For the most part, this pattern is not present when controls for incumbent hospital characteristics are included in the entry equation, suggesting substantial multicollinearity among the control variables and the instrument for entry (potential entrants). Furthermore, the differences between the medium and high markets in the analyses without controls are never significant. At best, there is only limited evidence that is consistent with entry deterrence, and no evidence that conclusively demonstrates its existence.

To rule out the possibility of alternate explanations for nonmonotonic investment patterns, two additional exercises to pursue are a falsification analysis, and an investigation into the variation in growth rates across market types during the pre-shock period. First, performing both stages of the analysis on a procedure that does not satisfy the criteria described in section 4.1 would help rule out concerns that nonmonotonic growth patterns arise for reasons other than entry deterrence. Second, although the empirical method I use is not conducive to a differences-in-differences approach that controls for pre-shock growth trends because markets switch groups over time, it would be reassuring to find weaker nonmonotonic investment patterns prior to the profitability shocks, and no evidence of U-shaped patterns in the pre-shock years, which would indicate regression to the mean during the post-shock periods.

All of the shocks I study occurred in the late 1980s, post-PPS but pre-managed care, which substantially intensified the downward pressure on hospital margins. The value of market leadership has increased dramatically in this newly competitive industry, forcing hospitals to weight the strategic impact of their actions more heavily in their decision-making processes. The role of entry deterrence in hospital decisions has likely increased since the study period.

Before concluding, I address a question of paramount importance to the entry-deterrence hypothesis: does it work? To answer this question, I look at the incidence of entry within the medium markets themselves. A finding of less entry among those markets that generated the largest volume growth between t=1 and t=2 would vindicate the entry

deterrence strategy. Table 13 lists the number of markets classified in the medium entry-probability group for each definition presented in the case studies, as well as the number of markets that experienced entry within each of these groups. The table breaks the data down further into those markets with incumbent growth rates above the 75th percentile, and those below. Although the numbers are rather small, the story is consistent: entry deterrence works. In 11 of the 12 medium groupings, entry rates for markets with the top 25% of growth rates were lower than rates for markets in the bottom 75%.

9 Conclusion

Hospital behavior is extremely difficult to study using traditional methods. The obfuscation of the pricing mechanism and the difficulty in measuring quality necessitate a creative approach to uncovering all actions, let alone strategic ones. Entry into new services is one of the few clear indicators of hospital decisions, and has therefore attracted attention in the health economics and industrial organization literatures. Although several researchers have investigated the reduced-form relationship between Herfindahl-type measures of hospital competition and service offerings (the "medical arms race" hypothesis), few have studied strategic interactions among players in local hospital markets.

Focusing on what is arguably the most important and most accessible measure of quality at the procedure level, hospital volume, this paper asks whether hospitals invest in quality in order to "solidify their market position" – i.e., to deter entry. The new trend in self-proclaimed "centers of excellence" may be a formalization of this strategy. By combining simple models of patient demand, quality production, and differentiated product market competition, I am able to generate clear theoretical predictions regarding entry deterrence through volume growth. I test this model on three distinct procedures, exploiting cross-sectional variation in geographic markets for each procedure. The identifying assumption is that procedure growth rates should increase monotonically in market potential unless hospitals engage in entry-deterring investment. Such investment, manifested in procedure growth rates, should be largest where entry deterrence is likeliest to impact entry decisions: in markets of intermediate attractiveness. When entry deterrence is sufficiently strong, these markets will grow at significantly faster rates than markets with either low or high market potential, simply because incumbents in these markets have a greater expected payoff for

investments that are observed by potential entrants prior to making their entry decisions.

The three case studies presented in this paper provide weak support for the hypothesis that hospitals manipulate volumes for strategic effect. Small sample sizes, noisy data, and multicollinearity among the instrument for entry and the control variables preclude a definitive conclusion. More recent data will help to determine whether strategic actions have become more widespread in the wake of heightened competition.

An analysis of the welfare effects of entry deterrence in surgical procedure markets, while beyond the scope of this paper, is an important next step for future research.

Table 1. Descriptive Statistics: Hospitals

Characteristic	EPS Providers	Liver Transplant Providers	Prostatectomy Providers	All US Hospitals
Ownership				
For-profit	6%	3%	8%	14%
Government	13%	32%	11%	28%
Not-for-profit	81%	65%	81%	58%
Facilities/Features				
CT scanner	98%	97%	97%	65%
Cath lab	91%	96%	73%	23%
Open heart surgery	79%	96%	53%	15%
Transplant program (any organ)	37%	100%	22%	7%
Cancer program	67%	79%	59%	20%
Radiation therapies	63%	83%	51%	16%
High surgical volume	91%	97%	81%	24%
Teaching hospital	38%	82%	23%	6%
Size				
Number of beds	473 (218)	607 (261)	401 (196)	172 (172)
N	626	94	1219	5385

Notes:

(1) Providers of radiation therapy are those hospitals that offer all three of the therapeutic radiation services included in the AHA survey: radioactive implants, megavoltage radiation, and radioisotope facilities.

(2) High surgical volume is 3000+ surgeries per year (approximately the 75th percentile for hospitals performing surgery).

Table 2. Descriptive Statistics: Metropolitan Statistical Areas

Variable	EPS (20% sample)	Liver Transplants	Prostatectomy (20% sample)
Number of incumbents, t=1	2.52 (2.72)	1.32 (0.58)	3.26 (3.93)
Entry (any) between t=1 and t=3	.542 (.500)	.297 (.463)	.388 (.488)
Number of entrants between t=1 and t=3	1.14 (1.55)	0.46 (0.84)	1.03 (2.25)
Number of entrants between t=1 and t=2	0.32 (0.64)	0.14 (0.35)	0.29 (0.84)
1990 population (in 100,000s)	9.95 (13.1)	22.1 (20.7)	6.76 (10.7)
Access to care, t=1	0.41 (0.30)	0.14 (0.20)	0.71 (0.41)
Incumbent volume in 1988	9.32 (13.4)	30.6 (37.9)	4.95 (6.88)
Incumbent volume in 1989	12.56 (19.1)	42.6 (46.8)	5.37 (8.14)
Incumbent volume in 1990	17.87 (24.3)	52.2 (54.5)	7.59 (9.94)
Incumbent volume in 1991	20.91 (26.9)	57.7 (60.0)	12.7 (18.1)
Incumbent volume in 1992	24.66 (32.6)	61.2 (67.8)	17.0 (23.2)
Incumbent volume in 1993	24.61 (34.5)	65.9 (65.1)	13.3 (17.0)
Incumbent volume in 1994	26.17 (36.0)	70.9 (65.9)	11.4 (14.2)
Incumbent volume in 1995	27.58 (39.1)	73.5 (66.4)	10.4 (12.9)
Incumbent volume in 1996	28.7 (41.2)	72.4 (65.3)	10.3 (14.0)
Incumbent volume growth, t=1 to t=2	0.40 (1.19)	0.70 (1.03)	.11 (1.03)
Potential entrants with:			
Teaching program	0.79 (1.91)	5.38 (6.09)	0.39 (1.33)
Cath lab	2.74 (3.63)		
Open heart surgery	1.53 (2.19)		
Cath lab & open heart surgery	**1.52 (2.17)**		
Transplant program		3.95 (2.89)	
Transplant & teaching programs		**2.05 (2.17)**	
Cancer & transplant program		2.38 (2.15)	
Cancer program			0.90 (2.36)
Radioactive implants			**0.98 (2.34)**
High surgical volume			1.20 (2.78)
Incumbent controls			
Fraction for-profit	.04 (.17)	0 (0)	.07 (.19)
Fraction government-owned	.17 (.31)	.36 (.47)	.12 (.27)
Fraction not-for-profit	.79 (.34)	.64 (.47)	.81 (.32)
Fraction teaching	.43 (.42)	.92 (.25)	.18 (.29)
Annual surgical operations	7409 (3256)	11201 (4944)	5647 (2323)
Beds	491 (174)	705 (281)	391 (132)
Experience	3.10 (1.22)	n/a	3.30 (1.15)
Fraction with cath lab and open heart surgery	.85 (.29)		
Fraction with cancer program		.86 (.30)	
Fraction with radiation therapies			.56 (.38)
N	155	37	273

Table 2 Notes

(1) Access to care = number of incumbents in t=1/1990 MSA population in 100,000s
(2) Incumbent volume growth is missing for MSAs with zero recorded procedures in t=1. There are 28 such MSAs in the EPS sample, and 50 in the prostatectomy sample.
(3) High surgical volume is 3000+ surgeries per year (approximately the 75th percentile for all hospitals performing surgery).
(4) Experience = mean number of years in sample since 1984
(5) Data on radiation therapies is missing for hospitals in two of the prostatectomy markets.
(6) The potential entrants measure used in the first-stage regression for each case study is bolded.

Table 3. Unadjusted Incumbent Growth Rates between t=1 and t=2, by Market Type

	EPS (N=127)		**Liver** (N=37)		**Prostatectomy** (N=222)	
	Def. 1	Def. 2	Def. 1	Def. 2	Def. 1	Def. 2
Market classification (no controls)						
Low	.219	.396	.562	.475	.076	.012
	(.139)	(.193)	(.202)	(.245)	(.090)	(.113)
Medium	.694	.455	1.089	1.048	.400	.287
	(.293)	(.206)	(.418)	(.331)	(.198)	(.123)
High	.348	.348	.445	.445	-.060	-.060
	(.127)	(.127)	(.199)	(.199)	(.082)	(.082)
Market classification (all controls)						
low	.322	.399	.877	.757	.172	.048
	(.162)	(.223)	(.297)	(.338)	(.109)	(.113)
medium	.447	.372	.751	.909	.113	.279
	(.252)	(.185)	(.341)	(.304)	(.128)	(.127)
high	.431	.431	.380	.380	.001	.001
	(.155)	(.155)	(.192)	(.192)	(.111)	(.111)

Notes:
(1) Standard errors are in parentheses.
(2) MSAs are classified into market groups using predicted entry probabilities from the first-stage regressions presented in tables 4,7, and 10. There are two first-stage equations: one with controls for incumbent characteristics, and one without. Boundaries for the definitions are given in Tables 5,8, and 11.

Table 4. EPS Case Study, First Stage Results

Dependent Variable = Entry in MSA after 1988 (Probit)		
	(1)	(2)
Potential entrants	.370 (.068)***	.380 (.072)***
Potential entrants squared	-.019 (.007)***	-.020 (.008)***
Mean years of incumbent experience	-.074 (.041)*	-.089 (.043)**
Access to care	-.507 (.228)**	-.534 (.249)**
Hospital controls	N	Y
Initial volume control	N	Y
N	155	155
Pseudo-R^2	.39	.45

Notes:

(1) Coefficients are translated to represent dF/dx

(2) Potential entrants are area hospitals with cath labs and open-heart surgery programs, but no EPS facilities.

(3) Mean years of incumbent experience = mean number of years in sample since 1984

(4) Access to care = number of incumbents in 1988/MSA population in 100,000s

(5) Hospital controls are: the fraction of incumbents in each ownership category (government, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents with cath labs and open heart surgery programs, mean number of beds for incumbents, mean number of surgical operations for incumbents.

(6) Initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 5. EPS Case Study, Market Definitions

	Definition 1			Definition 2		
Market classification	Probability Range	N	% entry	Probability Range	N	% entry
(no controls)						
Low	Pr<.35	57	19.3	Pr<.25	32	9.4
Medium	.35-.75	43	51.2	.25-.75	68	44.1
High	>.75	55	92.7	>.75	55	92.7
(all controls)						
Low	Pr<.35	57	15.8	Pr<.25	37	10.8
Medium	.35-.75	41	51.2	.25-.75	61	42.6
High	>.75	57	94.7	>.75	57	94.7

Note: Entry probabilities are predicted using the coefficients in Table 4.

Table 6. EPS Case Study, Second Stage Results

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type				
	Definition 1		*Definition 2*	
N=127, mean(y) = .40	(1)	(2)	(3)	(4)
Medium	.721**	.357	.295	.353
	(.309)	(.333)	(.387)	(.409)
High	.488	.405	.277	.499
	(.329)	(.351)	(.450)	(.478)
Access to care	.788*	.596	.513	.663
	(.468)	(.464)	(.523)	(.519)
Incumbent experience	.013	.055	.021	.075
	(.083)	(.087)	(.086)	(.090)
Hospital characteristics	N	Y	N	Y
Initial volume control	N	Y	N	Y
Adjusted R^2	.02	-.02	-.02	-.02

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Probability of Entry		
N=127, mean(y) = .40	(1)	(2)
Probability of entry	3.227*	1.667
	(.914)	(1.763)
Probability of entry	-2.100	-1.056
squared	(1.497)	(1.413)
Access to care	1.203**	.741
	(.598)	(.557)
Incumbent experience	.040	.074
	(.086)	(.090)
Hospital characteristics	N	Y
Initial volume control	N	Y
Adjusted R^2	.00	-.02

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type, Defined by Thirds of Potential Entrant Distribution or Population Distribution				
	Potential Entrant Thirds		*Population Thirds*	
N=127, mean(y) = .40	(1)	(2)	(3)	(4)
Medium (2^{nd} third)	.709*	.725**	.573*	.941**
	(.277)	(.284)	(.336)	(.338)
High (3^{rd} third)	.496	.476	1.038***	1.811***
	(.318)	(.325)	(.374)	(.418)
Access to care	.644	.640	1.210**	1.823**
	(.426)	(.442)	(.492)	(.509)
Incumbent experience	-.018	.033	-.028	.040
	(.085)	(.088)	(.082)	(.081)
Hospital characteristics	N	Y	N	Y
Initial volume control	N	Y	N	Y
Adjusted R^2	.02	.02	.04	.12

Table 6 Notes

(1) Access to care = number of incumbents in 1988/ MSA population in 100,000s
(2) Mean years of incumbent experience = mean number of years in sample since 1984
(3) Hospital controls are: the fraction of incumbents in each ownership category (government, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents with cath labs and open heart surgery programs, mean number of beds for incumbents, mean number of surgical operations for incumbents.
(4) Low initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 7. Liver Transplant Case Study, First Stage Results

Dependent Variable = Entry in MSA after 1989 (Probit)		
	(1)	(2)
Potential entrants	-.016 (.105)	.032 (.136)
Potential entrants squared	.011 (.016)	.020 (.028)
Access to care	-2.102 (1.106)	-.323 (1.055)
Hospital controls	N	Y
Initial volume control	N	Y
N	37	33
Pseudo-R^2	.25	.41

Notes:
(1) Coefficients are translated to represent dF/dx
(2) Potential entrants are area hospitals with teaching and transplant facilities, but no *liver* transplant program.
(3) Access to care = number of incumbents in 1989/ MSA population in 100,000s
(4) Hospital controls are: the fraction of incumbents in each ownership category (government, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents with cancer programs, mean number of beds for incumbents, mean number of surgical operations for incumbents.
(5) Initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 8. Liver Transplant Case Study, Market Definitions

	Definition 1			Definition 2		
Market classification	Probability Range	N	% entry	Probability Range	N	% entry
(no controls)						
Low	Pr<.2	14	14.3	Pr<.15	11	18.2
Medium	.2-.4	12	25.0	.15-.4	15	20.0
High	>.4	11	54.6	>.4	11	54.6
(all controls)						
Low	Pr<.2	17	5.9	Pr<.15	13	0.0
Medium	.2-.4	9	22.2	.15-.4	13	23.1
High	>.4	11	72.7	>.4	11	72.7

Note: Entry probabilities are predicted using the coefficients in Table 8.

Table 9. Liver Transplant Case Study, Second Stage Results

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type				
	Definition 1		*Definition 2*	
N=37, mean(y) = .70	(1)	(2)	(3)	(4)
Medium	.874*	-.061	1.073**	.263
	(.433)	(.478)	(.450)	(.524)
High	.276	-.309	.542	-.060
	(.453)	(.470)	(.492)	(.564)
Access to care	1.734*	.581	2.109**	.673
	(.963)	(1.130)	(.991)	(1.138)
Hospital characteristics	N	Y	N	Y
Initial volume control	N	Y	N	Y
Adjusted R^2	.08	.20	.12	.20

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Probability of Entry		
N=37, mean(y) = .70	(1)	(2)
Probability of entry	3.996	-.489
	(2.868)	(2.410)
Probability of entry	-3.822	.021
squared	(2.775)	(2.334)
Access to care	2.144*	.492
	(1.208)	(1.161)
Hospital characteristics	N	Y
Initial volume control	N	Y
Adjusted R^2	.01	.20

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type, Defined by Thirds of Potential Entrant Distribution or Population Distribution				
	Potential Entrant Thirds		*Population Thirds*	
N=37, mean(y) = .70	(1)	(2)	(3)	(4)
Medium (2nd third)	-.710	-.147	1.017**	.968**
	(.410)	(.434)	(.429)	(.403)
High (3rd third)	-.397	-.082	.222	.223
	(.467)	(.508)	(.451)	(.463)
Access to care	.507	.838	1.739*	1.329
	(.901)	(1.127)	(.940)	(1.097)
Hospital characteristics	N	Y	N	Y
Initial volume control	N	Y	N	Y
Adjusted R^2	.05	.27	.14	.37

Notes:
(1) Access to care = number of incumbents in 1988/ MSA population in 100,000s
(2) Hospital controls are: the fraction of incumbents in each ownership category (government, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents with cancer programs, mean number of beds for incumbents, mean number of surgical operations for incumbents.
(3) Low initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 10. Prostatectomy Case Study, First Stage Results

Dependent Variable = Entry in MSA after 1988 (Probit)		
	(1)	(2)
Potential entrants	.306 (.051)***	.321 (.056)***
Potential entrants squared	-.015 (.003)***	-.016 (.003)***
Mean years of incumbent experience	-.058(.031)*	-.059 (.034)*
Access to care	-.642(.130)***	-.636 (.139)***
Hospital controls	N	Y
Low initial volume control	N	Y
N	273	271
Pseudo-R^2	.41	.46

Notes:
(1) Coefficients are translated to represent dF/dx
(2) Potential entrants are area hospitals that perform radioactive implants, but not prostatectomy.
(3) Mean years of incumbent experience = mean number of years in sample since 1984
(4) Access to care = number of incumbents in 1988/ MSA population in 100,000s
(5) Hospital controls are: the fraction of incumbents in each ownership category (govt, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents that offer radiation therapies, mean number of beds for incumbents, mean number of surgical operations for incumbents.
(6) Low initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 11. Prostatectomy Case Study, Market Definitions

	Definition 1			Definition 2		
Market classification	Probability Range	N	% entry	Probability Range	N	% entry
(no controls)						
Low	Pr<.35	162	11.1	Pr<.25	100	8.0
Medium	.35-.75	59	64.4	.25-.75	121	39.7
High	>.75	52	96.2	>.75	52	96.2
(all controls)						
Low	Pr<.35	148	10.8	Pr<.25	117	6.8
Medium	.35-.75	66	53.0	.25-.75	95	44.3
High	>.75	57	96.5	>.75	57	96.5

Note: Entry probabilities are predicted using the coefficients in Table 10.

Table 12. Prostatectomy Case Study, Second Stage Results

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type				
	Definition 1		*Definition 2*	
N=222, mean(y) = .11	(1)	(2)	(3)	(4)
Medium	.306	-.230	.299	.252
	(.203)	(.220)	(.213)	(.220)
High	-.150	-.340	-.031	.049
	(.209)	(.252)	(.264)	(.278)
Access to care	-.172	-.458**	-.092	-.171
	(.199)	(.216)	(.235)	(.231)
Incumbent experience	.113*	.097	.123*	.123*
	(.061)	(.064)	(.063)	(.065)
Hospital characteristics	N	N	Y	Y
Initial volume control	N	N	Y	Y
Adjusted R^2	.03	.03	.02	.03

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Probability of Entry		
N=222, mean(y) = .11	(1)	(2)
Probability of entry	2.517*	.775
	(1.344)	(1.200)
Probability of entry	-2.231**	-.750
squared	(1.122)	(.976)
Access to care	.169	-.195
	(.309)	(.290)
Incumbent experience	.141**	.121*
	(.064)	(.067)
Hospital characteristics	N	Y
Initial volume control	N	Y
Adjusted R^2	.02	.02

OLS Regression of Incumbent Growth Rate between t=1 and t=2 on Market Type, Defined by Thirds of Potential Entrant Distribution or Population Distribution				
	Potential Entrant Thirds		*Population Thirds*	
N=222, mean(y) = .11	(1)	(2)	(3)	(4)
Medium (2nd third)	.265	.284	.515***	.495**
	(.190)	(.194)	(.198)	(.204)
High (3rd third)	-.087	-.057	.066	.120
	(.196)	(.207)	(.214)	(.257)
Access to care	-.200	-.249	-.121	-.135
	(.180)	(.182)	(.209)	(.213)
Incumbent experience	.119**	.128**	.120**	.125**
	(.060)	(.063)	(.058)	(.061)
Hospital characteristics	N	Y	N	Y
Initial volume control	N	Y	N	Y
Adjusted R^2	.02	.03	.05	.05

Notes:

(1) Access to care = number of incumbents in 1988/ MSA population in 100,000s

(2) Mean years of incumbent experience = mean number of years in sample since 1984

(3) Hospital controls are: the fraction of incumbents in each ownership category (government, not-for-profit, for-profit), the fraction of incumbents that are teaching hospitals, the fraction of incumbents that offer radiation therapies, mean number of beds for incumbents, mean number of surgical operations for incumbents.

(4) Low initial volume control is a dummy for total incumbent volume <=5 procedures in t=1.

* signifies p<=.10, ** signifies p<=.05, *** signifies p<.01

Table 13. Incidence of Entry within Medium-Probability Markets, by Percentile of Incumbent Growth Rate

Case	Definition		Total	Top 25%	Bottom 75%
Market classification (no controls)					
EPS	1	N	35	8	27
		# entrants	19	3	16
		% entry	54	38	59
	2	N	54	12	42
		# entrants	26	6	20
		% entry	48	50	48
LIVER	1	N	12	3	9
		# entrants	3	0	3
		% entry	25	0	33
	2	N	15	3	12
		# entrants	3	0	3
		% entry	20	0	25
PROST	1	N	45	10	35
		# entrants	31	6	25
		% entry	69	60	71
	2	N	94	16	78
		# entrants	38	6	32
		% entry	40	38	41
Market classification (all controls)					
EPS	1	N	34	8	26
		# entrants	18	4	14
		% entry	53	50	54
	2	N	51	12	39
		# entrants	22	5	17
		% entry	43	42	44
LIVER	1	N	9	2	7
		# entrants	2	0	2
		% entry	22	0	29
	2	N	13	3	10
		# entrants	3	0	3
		% entry	23	0	30
PROST	1	N	54	13	41
		# entrants	26	6	20
		% entry	48	46	49
	2	N	77	19	58
		# entrants	33	8	25
		% entry	43	42	43

Note: The 25th percentile is calculated for each definition-procedure pair, using only the incumbent growth rates for medium markets. Total figures differ from those presented in the market definition tables because several of the markets have missing growth rates (due to a volume total of 0 in t=1).

Figure 1. Incumbent Investment Patterns

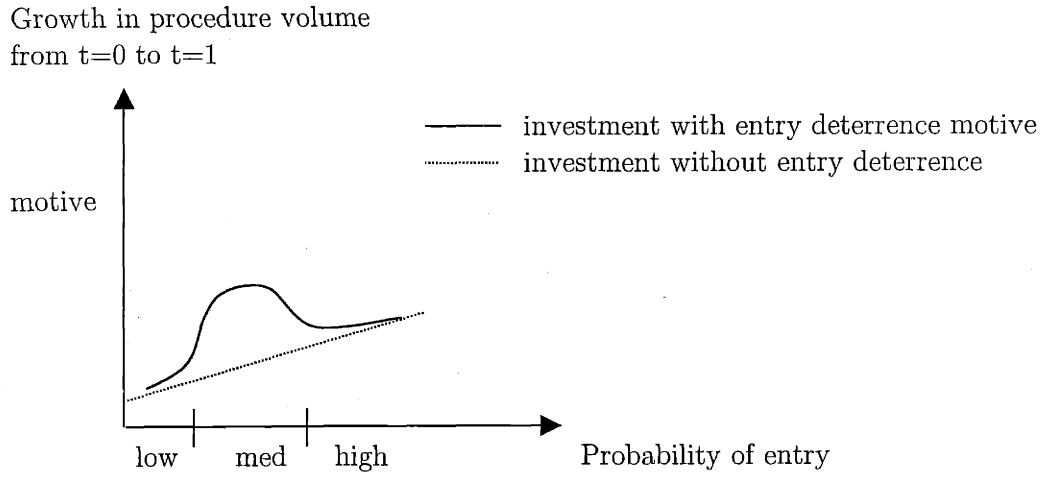


Figure 2. EPS: Medicare Volumes, 1984-1996

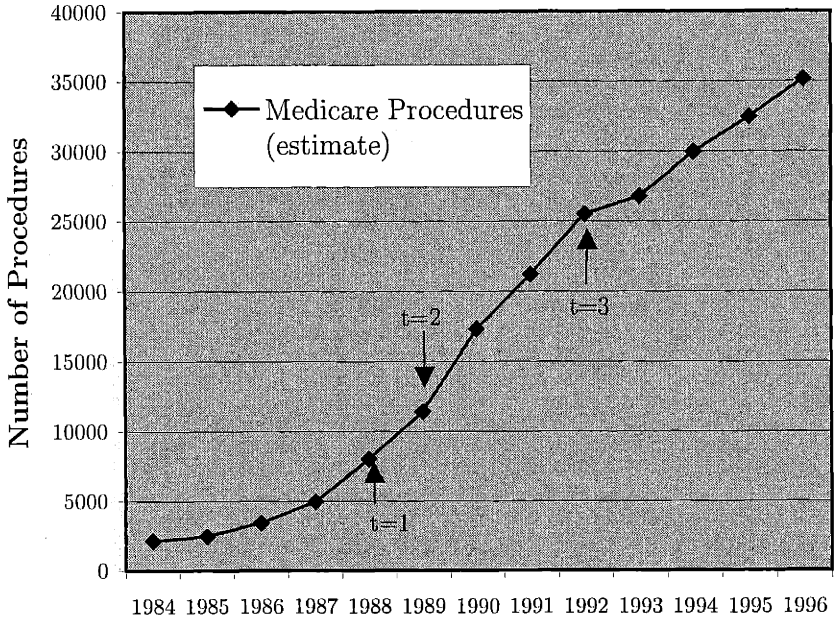


Figure 3. Liver Transplants: Total and Medicare Volumes, 1985-1998

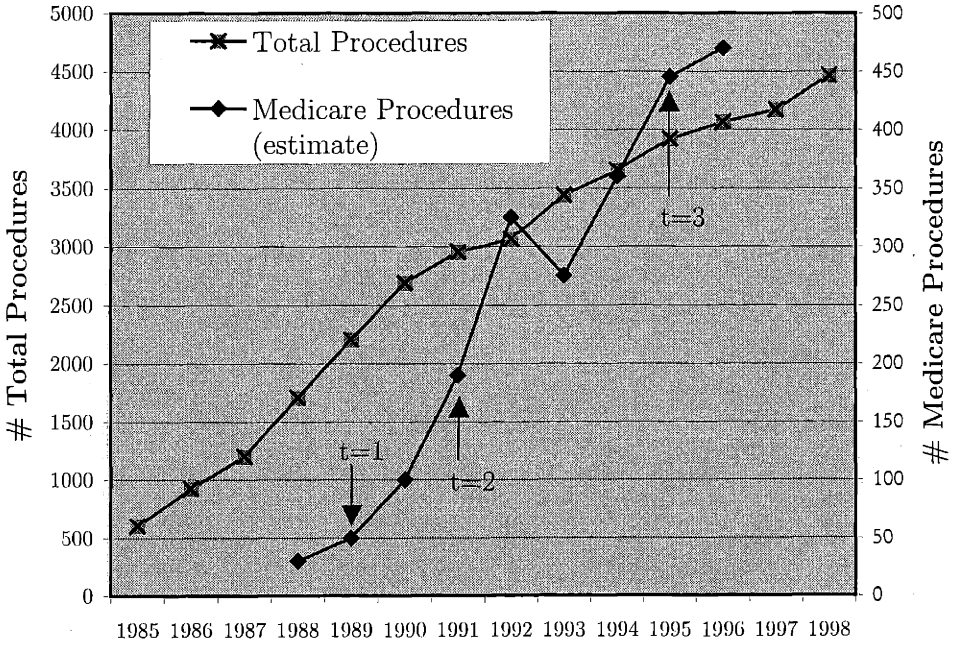


Figure 4. Prostatectomy: Medicare Volumes, 1984-1996

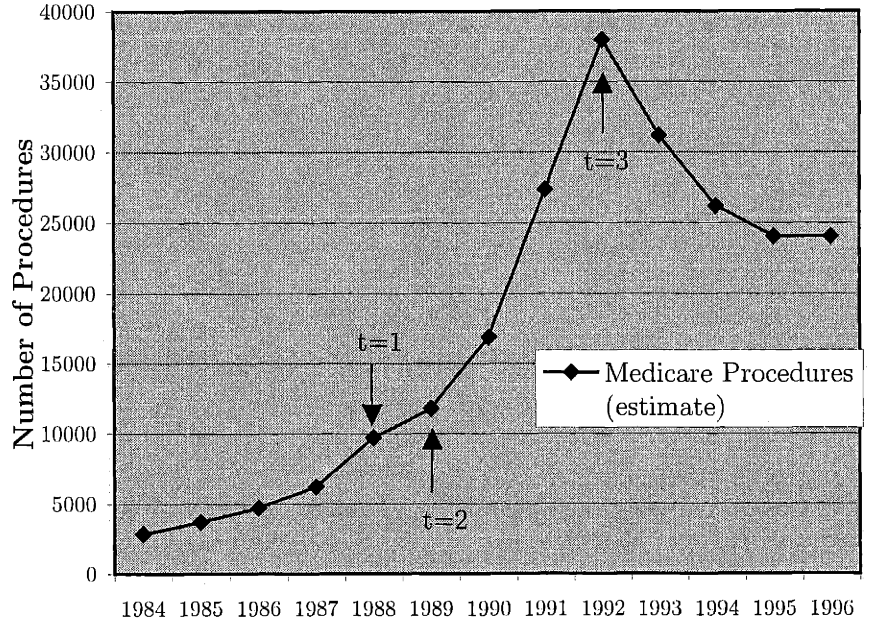


Figure 5. Adjusted EPS Growth Rates
vs. Predicted Entry Probability

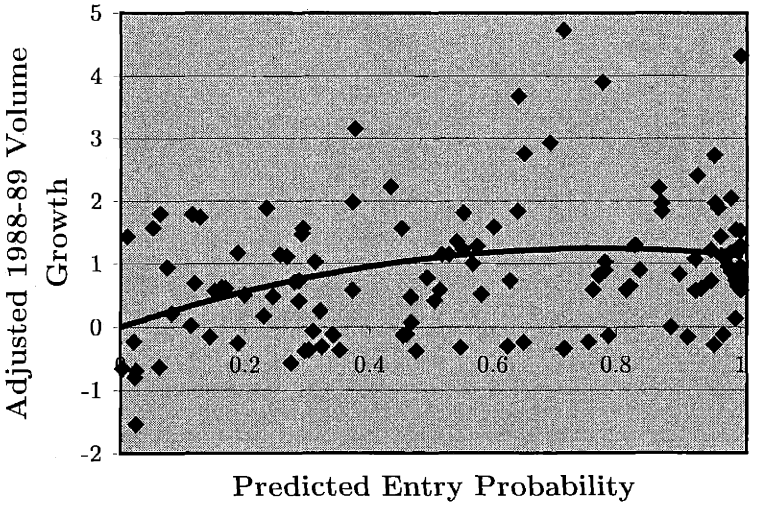


Figure 6. Adjusted Liver Transplant Growth Rates
vs. Predicted Entry Probability

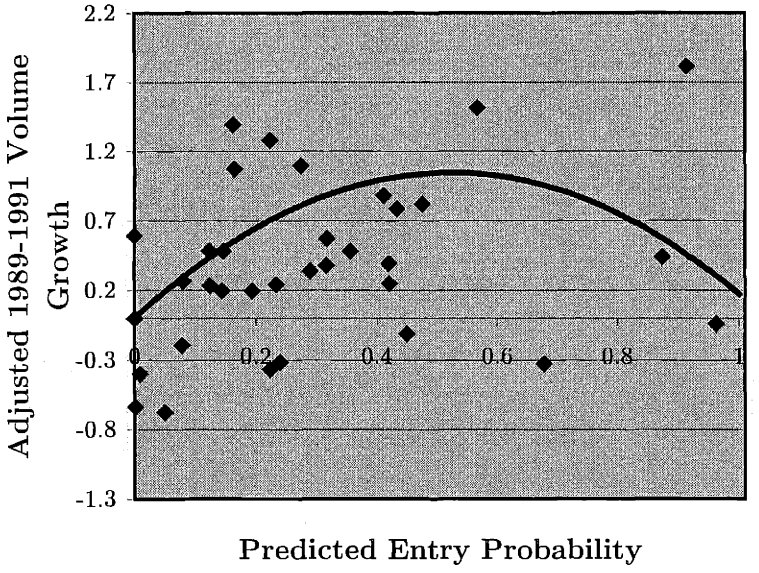
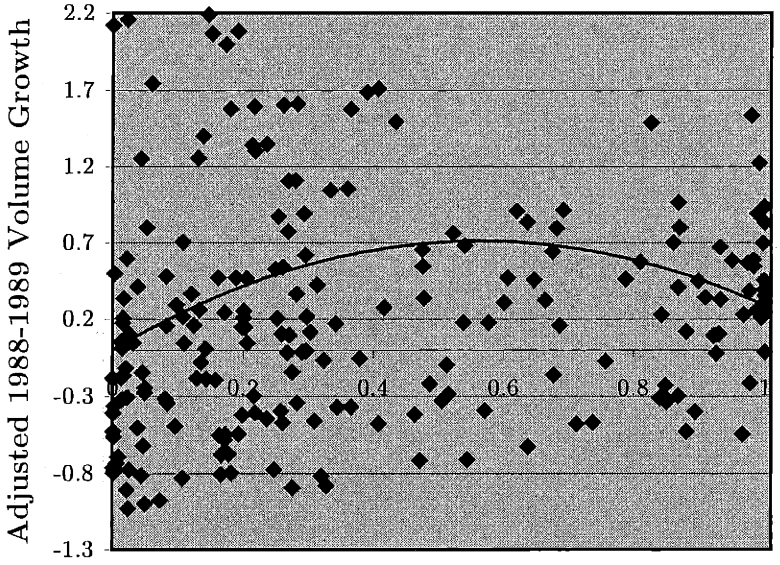


Figure 7. Adjusted Prostatectomy Growth Rates
vs. Predicted Entry Probability



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Appendix A

Suppose the demand function is $Q_t^i = l_t^i - \gamma \sum_{-i} l_t^{-i}$, the usual Bertrand differentiated-product specification. Suppose further that quality is produced with a Cobb-Douglas technology, $l_t^i = (k_t^i)^\alpha (Q_0 + \Sigma_{j=1}^{t-1} Q_j^i)^{1-\alpha}$, where Q_0 is a small positive constant that is the same for all hospitals and $0 < \alpha < 1$. The cost of investment is given by $C_t^i = r_t k_t^i$. The entrant solves

$$\max_{k_2^{D_E}} \; P\left[(k_2^{D_E})^\alpha (Q_0)^{1-\alpha} - \gamma (k_2^{*D_M})^\alpha (Q_0 + Q_1^M(k_1^{*M}))^{1-\alpha}\right] - r_2 k_2^{D_E}$$

to obtain $k_2^{*D_E} = Q_0 \left(\frac{\alpha P}{r_2}\right)^{\frac{1}{1-\alpha}}$ and $\pi_2^{*D_E} = P\left[Q_0 \left(\frac{\alpha P}{r_2}\right)^{\frac{\alpha}{1-\alpha}} - \gamma (k_2^{*D_M})^\alpha (Q_0 + Q_1(k_1^{*M}))^{1-\alpha}\right] - r_2^\alpha Q_0 (\alpha P)^{\frac{1}{1-\alpha}}$. By symmetry, $k_2^{*D_M} = \left(Q_0 + Q_1^M(k_1^{*M})\right)\left(\frac{\alpha P}{r_2}\right)^{\frac{1}{1-\alpha}}$, and by definition, $Q_1^M = (k_1^{*M})^\alpha (Q_0)^{1-\alpha}$. I can now sign the components in $\left[\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M} + \frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}} \cdot \frac{dk_2^{D_M^*}}{dk_1^M}\right]$, which determines whether the incumbent will overinvest or underinvest to deter entry. $\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M} = \frac{\partial \pi_2^{D_E^*}}{\partial Q_1^M} \cdot \frac{dQ_1^M}{dk_1^M} < 0$, $\frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}} < 0$, and $\frac{dk_2^{D_M^*}}{dk_1^M} > 0$. The intuition for $\frac{\partial \pi_2^{D_E^*}}{\partial k_1^M} < 0$ and $\frac{\partial \pi_2^{D_E^*}}{\partial k_2^{D_M}} < 0$ is simply that better quality on the part of a competitor erodes profits in a differentiated-products setting. The intuition for $\frac{dk_2^{D_M^*}}{dk_1^M} > 0$ is that the marginal product of $k_2^{D_M}$ increases with first-period volume, which in turn is an increasing function of k_1^M. The result is that the monopolist will overinvest in k_1^M to deter entry.

Appendix B

This appendix summarizes the monotonicity result presented in Ellison and Ellison (2000), as applied to the model outlined in section 3. A more precise exposition can be found in the original source.

Without entry-deterrence motives, the first-order condition for $k_1^{M^*}(z)$ is

$$\begin{aligned} -\frac{\partial \pi_1^{M^*}}{\partial k_1^M}(k_1^{M^*}(z), z) \;=\; & F(\pi_2^{D_E^*}(k_1^{M^*}(z), z) \cdot \frac{\partial \pi_2^{D_M^*}}{\partial k_1^M}(k_1^{M^*}(z), k_2^{D_E^*}(z), z) \\ & + (1 - F(\pi_2^{D_E^*}(k_1^{M^*}(z), z))) \cdot \frac{\partial \pi_2^{M^*}}{\partial k_1^M}(k_1^{M^*}(z), z) \end{aligned}$$

The strategic entry accommodation effect is already incorporated in the choice of $k_1^{M^*}(z)$ (compare with the first-order condition in section 3.2, where $\frac{\partial \pi_2^{D_M}}{\partial k_1^M}$ are $\frac{\partial \pi_2^M}{\partial k_1^M}$ used).

Differentiating this expression with respect to z yields

$$
\begin{aligned}
-\frac{\partial^2 \pi_1^{M^*}}{\partial z \partial k_1^M} - \frac{\partial^2 \pi_1^{M^*}}{\partial (k_1^M)^2} \cdot \frac{dk_1^{M^*}}{dz} \;=\; & F(\pi_2^{D_E^*}) \cdot \left(\frac{\partial^2 \pi_2^{D_M^*}}{\partial (k_1^M)^2} \cdot \frac{dk_1^{M^*}}{dz} + \frac{\partial^2 \pi_2^{D_M^*}}{\partial k_2^{D_E^*} \partial k_1^M} \cdot \frac{dk_2^{D_E^*}}{dz} + \frac{\partial^2 \pi_2^{D_M^*}}{\partial z \partial k_1^M} \right) \\
& + (1 - F(\pi_2^{D_E^*})) \cdot \left(\frac{\partial^2 \pi_2^{M^*}}{\partial (k_1^M)^2} \cdot \frac{dk_1^{M^*}}{dz} + \frac{\partial^2 \pi_2^{M^*}}{\partial z \partial k_1^M} \right) \\
& + f(\pi_2^{D_E^*}) \cdot \frac{d\pi_2^{D_E^*}}{dz} \cdot \left(\frac{\partial \pi_2^{D_M^*}}{\partial k_1^M} - \frac{\partial \pi_2^{M^*}}{\partial k_1^M} \right)
\end{aligned}
$$

Solving for $\frac{dk_1^{M^*}}{dz}$ produces

$$
\frac{dk_1^{M^*}}{dz} = \frac{\begin{array}{c} \left[F(\pi_2^{D_E^*}) \cdot \left(\frac{\partial^2 \pi_2^{D_M^*}}{\partial k_2^{D_E^*} \partial k_1^M} \cdot \frac{dk_2^{D_E^*}}{dz} + \frac{\partial^2 \pi_2^{D_M^*}}{\partial z \partial k_1^M} \right) + (1 - F(\pi_2^{D_E^*})) \cdot \left(\frac{\partial^2 \pi_2^{M^*}}{\partial z \partial k_1^M} \right) + \frac{\partial^2 \pi_1^{M^*}}{\partial z \partial k_1^M} \right] \\ + f(\pi_2^{D_E^*}) \cdot \frac{d\pi_2^{D_E^*}}{dz} \cdot \left[\frac{\partial \pi_2^{D_M^*}}{\partial k_1^M} - \frac{\partial \pi_2^{M^*}}{\partial k_1^M} \right] \end{array}}{-\frac{\partial^2 \pi_1^{M^*}}{\partial (k_1^M)^2} - F(\pi_2^{D_E^*}) \cdot \frac{\partial^2 \pi_2^{D_M^*}}{\partial (k_1^M)^2} - (1 - F(\pi_2^{D_E^*})) \cdot \frac{\partial^2 \pi_2^{M^*}}{\partial (k_1^M)^2}}
$$

Due to the concavity assumptions for the profit functions, the denominator of this expression is always positive. Given the earlier assumption of $\frac{d\pi_2^{D_E^*}}{dz} > 0$, $k_1^{M^*}(z)$ is monotone nondecreasing (nonincreasing) in z if both bracketed terms in the numerator are nonnegative (nonpositive). Ellison and Ellison label the first term the "direct effect" of z on $k_1^{M^*}$; it is positive if increasing z raises marginal profits more than it raises marginal investment costs. The second bracketed term is the "competition effect," which is nonnegative if the marginal duopoly profits associated with an additional unit of $k_1^{M^*}$ exceed or equal the marginal monopoly profits.

Continuing the example presented in Appendix A, suppose that z is simply a multiplicative constant in the demand function, so $Q_t^{i'} = z \cdot \left(l_t^i - \gamma \sum_{-i} l_t^{-i} \right)$. In this case, the "direct effect" of z is clearly positive, because a larger z not only raises the incumbent's expected profits, it *reduces* the cost of investing in $k_1^{M^*}$ in the first period. The "competition effect" is zero, since the marginal benefit to the incumbent of an additional unit of $k_1^{M^*}$ is the same regardless of the competitive scenario. This result is due to the specification of the demand function, which does not contain an interaction between l_t^i and l_t^{-i}; a stronger competitor damages profits, but does not affect the marginal benefit of l_t^i (and hence of $k_1^{M^*}$ or $k_2^{D_M^*}$). A demand function with an interaction between the two quality levels, such

as $Q_2^{D_M} = z \cdot \left(l_2^{D_M} - \gamma l_2^{D_E} + \theta (l_2^{D_M} - l_2^{D_E})^2 \right)$ and $Q_2^{D_E} = z \cdot \left(l_2^{D_E} - \gamma l_2^{D_M} - \theta (l_2^{D_M} - l_2^{D_E})^2 \right)$, would yield a positive competition effect.[22]

The final result in this setting is that $k_1^{M^*}(z)$ is monotone increasing in z when entry-deterrence motives are absent.

[22] Note $l_2^{D_M^*}$ will always be greater than $l_2^{D_E^*}$, hence the signs on the squared term.

Data Appendix

To construct the hospital samples for each case study, I begin with a dataset of all hospitals that are recorded as having performed at least one procedure between t=1 and t=3. I then drop children's and military or Veterans Administration hospitals, as these hospitals are unlikely to be affected by Medicare policy or to compete directly with general hospitals. The few hospitals not located in MSAs are also dropped because they cannot be classified using my market definition. In addition, to ensure that the hospitals classified as incumbents are serious providers of the service (so they might conceivably engage in entry-deterring behavior), I eliminate those that exit within a year of t=2 (that is, the first year in which potential entrants can theoretically enter the market). Finally, as described in section 5, I drop all EPS or prostatectomy providers performing fewer than 3 procedures cumulatively between 1984 and 1996 or having fewer than 200 beds.

Sample Selection: Hospitals

Procedure	EPS	Liver Transplants	Prostatectomy
Number of providers between t=1 and t=2	881	115	2513
- children's/military/VA hospitals	-1	-19	-2
- hospitals without matching data from AHA	-2		-3
- hospitas with fewer than 200 beds	-134		-1068
- hospitals exiting by (t=2)+1	-62	-2	-49
- hospitals performing <3 procedures cumulatively between 1984 and 1996	-39		-62
- hospitals not located in MSAs	-17		-110
Total sample size	626	94	1219

Does Public Insurance Improve the Efficiency of Medical Care? Medicaid Expansions and Child Hospitalizations

with Jonathan Gruber

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Abstract

One of the benefits commonly claimed for expanded public health insurance is improved efficiency of medical care delivery, but this claim has little rigorous empirical support. We provide such support by assessing the impact of the Medicaid expansions over the 1983-1996 period on the incidence of avoidable hospitalizations. We find that expanded public insurance eligibility leads to a significant decline in avoidable hospitalizations: over this period Medicaid eligibility expansions were associated with a 22% decline in avoidable hospitalization. But we also find that there is a countervailing and larger impact in terms of increased access to hospital care for newly eligible children, so that there is an overall 10% rise in child hospitalizations due to the expansions. The expansions have mixed implications for treatment intensity, but appear to be associated with a significant shift in the types of hospitals at which children are treated, with fewer children treated in public hospitals and more in for-profit facilities.

1 Introduction

The dramatic rise and high level of uninsurance rates in the U.S., despite an economic boom that has had only one interruption in 15 years, is striking. In 1987, 14.8% of non-elderly Americans were without health insurance. Over the next decade, the non-elderly population without insurance coverage grew by nearly 25% to 18.3%, so that in 1997 there were over 43 million uninsured Americans. Particularly troubling is the significant increase in the uninsurance rates of children in the U.S.; despite dramatic expansions of public health insurance through the Medicaid program since the mid-1980s, the share of children without health insurance has grown by over 10% since 1987, to 15% of children (Fronstin, 1998).

This rise in the uninsured concerns policy-makers for two reasons. The first is that insurance coverage is generally assumed to lead to better health. The second is that insurance coverage is generally assumed to lead to more efficient use of medical care. The presumption is that uninsured individuals will not only use more care when they become insured, but that care will be used more appropriately, for example by using physicians rather than emergency rooms for primary care.

There is a substantial literature assessing the first of these contentions, with both simple comparisons of individuals across insurance states and more sophisticated analyses of exogenous shifts in insurance coverage; see Gruber (1997) for an extensive review. But there is much less evidence on the second contention.

The purpose of our paper is to address this deficiency. We do so by exploring the impacts of the Medicaid expansions of the late 1980s and early 1990s, the largest change in public insurance policy over the past 30 years, on the nature of hospitalizations of children in the U.S. We consider the impact of Medicaid on both the total number of child hospitalizations, and the types of hospitalizations. We explore in particular whether the types of hospitalizations that have been denoted by medical experts as "avoidable" rise or fall as Medicaid is expanded. If Medicaid is increasing access to "more efficient" primary care, then we should observe a decline in these avoidable hospitalizations as Medicaid expands. In theory, since Medicaid is both increasing access for unavoidable

hospitalizations, but promoting efficiency that reduces avoidable hospitalizations, the net impact of expansions of the program on hospital use are ambiguous.

We focus our analysis on the hospitalization of children, the demographic group which has been the primary target group of public insurance policy over the past 15 years.[1] While much public policy attention has focused on children, the economics literature on hospitalization has largely ignored them; most work by economists on hospitalization has focused instead on adults and, in particular, the elderly. But children's hospitalizations represent 7% of the total, and 11% of hospital spending is devoted to children. Moreover, there has been a sharp decrease in the incidence of child hospitalization over the past 15 years, with rates falling by almost 50% since 1980, much more than for adults. This trend may be related to the high fraction of children's hospitalizations that is believed to be avoidable - 25 percent as compared to 10 percent for adults. As a result, children are a particularly interesting group to study in this context.

There are two key features of our empirical strategy. The first is the Medicaid expansions, which occurred over the period since 1984 at a very different pace across the states, and across different groups of children within states. This policy heterogeneity provides the exogenous variation in insurance status necessary to carry out our analysis. The second is our use of the National Hospital Discharge Survey (NHDS), the only nationally representative survey of hospital discharges. These data have large samples of child discharges for each year, as well as detailed information on admission diagnoses that allows us to assess the "avoidability" of hospitalizations. By matching our information on Medicaid eligibility to these data, we are able to assess the impact of insurance status on the number and type of hospitalizations.

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[1] There have also been substantial expansions in the coverage of the expenses of pregnancy; see Gruber (1997) for a review. But here the issues of efficiency are different, since virtually every pregnancy results in a hospitalization; rather, the question is whether mothers who gain insurance coverage see physicians earlier in their pregnancies, and if pregnancy outcomes improve as a result. For evidence that this is the case, see Currie and Gruber (1996a).

We find that extending Medicaid coverage to low-income children has substantially reduced the incidence of avoidable hospitalization, while increasing the rate of hospitalization overall. Between 1983 and 1996, Medicaid expansions led to 22 percent fewer avoidable pediatric hospitalizations, but 10 percent more hospitalizations overall. In addition, the expansions are associated with shorter hospital stays, but a higher number of procedures performed during those stays. They also appear to have significantly increased children's access to for-profit hospitals.

Our paper proceeds as follows. Section 2 provides background on child hospitalizations, avoidable hospitalizations, and the Medicaid expansions. Section 3 discusses our data and empirical strategy. Section 4 presents our results on total and avoidable hospitalizations. Section 5 then extends our analysis to consider what Medicaid has done to the nature of child hospitalization more generally, focusing on sources of insurance coverage, intensity of treatment, and the types of hospitals to which children are admitted. Section 6 concludes.

2 Background

2.1 Pediatric Hospitalizations

Accounting for 7.2% of all hospital admissions in 1996, pediatric hospitalizations are frequently overlooked in the health economics literature. Yet these hospitalizations were responsible for $20 billion in charges in 1987, the latest year for which data are available, representing 10.7% of hospital charges and nearly half of total expenditures on child health care services.[2] Moreover, recent public health insurance reforms have focused on extending coverage to impoverished children, highlighting the need to understand children's health and health care utilization patterns.

Figure 1 presents time trends in hospitalization rates in the U.S. for the under 15, 15 to 64, and 65 plus populations, estimated using the annual National Hospital Discharge Survey (NHDS). The disparity in hospitalization rates across age groups is large, with the over 65 population hospitalized 9 times as frequently as children (346 per 1,000 elderly vs. 38 per

[2] Tabulations from the National Medical Expenditure Survey, 1987, as reported in Hahn (1992). Estimates refer to children aged 0 to 17.

1,000 children). A marked decline in hospitalization rates during the 1980-1996 period is evident for both the 15-64 and the under 15 groups; the trend in the over 65 category fluctuates during this period, but due to the changing age composition of this group, this trend cannot be meaningfully compared to the trends in the younger groups. Overall, the hospitalization rate declined by 31%, with the relative decline for children (47%) the largest among the three groups.

Table 1 compares the leading causes of pediatric and adult hospitalizations, tabulated using the first-listed diagnosis code in the 1996 NHDS. The table highlights the obvious age-related patterns in hospital needs, with diseases of the respiratory system (asthma, pneumonia, and acute infections) topping the list for children, childbirth ranking first for adults 15-64, and diseases of the circulatory system (largely heart disease) accounting for the plurality of hospitalizations among the elderly. Infectious and parasitic diseases, along with the category of endocrine, nutritional, metabolic, and immunity disorders, account for the major afflictions specific to children.

Despite this wealth of statistical information on children's hospitalizations, there is little work by health policy analysts on the causal determinants of child hospitalization; the work that exists is largely descriptive in nature. McConnochie et. al (1997a) review the medical literature on pediatric hospitalizations, and draw two conclusions that are important for our purposes. First, there is a substantial amount of "inappropriateness" or "avoidability" in child hospitalization; we discuss this further below. Second, there is high geographic variation in hospitalization rates of children that is not easily explained by morbidity differences. In their own studies of hospitalization rates for infants of different socioeconomic backgrounds, the authors find that nearly 80 percent of the higher rates for disadvantaged infants is due to "discretionary" as opposed to "mandatory" conditions, suggesting that disease prevalence is not the only determinant of hospitalization. A study of infant hospitalizations for asthma by Homer et al. (1996) controls for morbidity burdens using measures of oxygen saturation in admitted patients, and finds that morbidity does not explain all of the differences in hospitalization rates between Boston and Rochester, New York. Goodman et al. (1994) investigate the effects of demand inducement and health system characteristics on pediatric discharges, concluding that discharges are

positively associated with bed supply, and negatively associated with distance from the hospital and residence near an academic medical center.

Finally, several studies have noted that hospitalization rates are higher for the uninsured and Medicaid populations, though these studies do not present separate estimates for children (e.g. Weissman et al., 1992; Billings and Teicholz, 1990). Only two studies of which we are aware, however, utilize a framework that addresses causality between insurance status and the probability of hospitalization for children. The RAND Health Insurance experiment (Manning et al., 1987) uses randomly assigned variation in copayment rates to show that there are insignificant increases in the probability of admission for children covered fully for inpatient expenses versus those covered by cost-sharing plans. On the other hand, Currie and Gruber (1996), using the Medicaid expansions studied here, find that becoming eligible for Medicaid nearly doubles the probability of hospitalization. The discrepancy between these findings may arise from the fact that the RAND experiment capped out-of-pocket exposure at a reasonably low level, so that in many cases those children covered by cost sharing plans were effectively fully insured for hospitalization.

2.2 Avoidable Hospitalizations

Defined as hospitalizations that "might not have occurred had [patients] received effective, timely, and continuous outpatient (ambulatory) medical care for certain chronic disease conditions," avoidable hospitalizations (AVHs) are commonly used as a measure of access to health care. As such, the list of AVH diagnoses is carefully selected so as to represent conditions more likely to result from inadequate access to ambulatory care, rather than from differences in disease prevalence or provider practices. The list is therefore distinct from so-called "discretionary" admissions, those for which subjective physician judgment is an integral part of the decision to admit.[3] For example, admissions for immunizable conditions are non-discretionary and avoidable, whereas admissions for acute fever are discretionary but unavoidable. Of course, as noted by Weissman, Gatsonis, and Epstein in

[3] McConnochie et al. (1997b).

their oft-cited 1992 JAMA article on AVH rates by insurance status, "being avoidable is a matter of degree." Nevertheless, the AVH rate is designed to capture the effectiveness of the health care system in providing timely care.

A list of pediatric AVH diagnoses is presented in Table 2. Of the 39.4 million pediatric hospitalizations that occurred between 1983 and 1996, 26 percent were classified as avoidable using this definition. The top 6 avoidable conditions are for asthma (24% of AVHs), pneumonia (23%), gastroenteritis (14%), ear, nose, and throat (ENT) infections (13%), dehydration (8%), and kidney/urinary tract infections (5%). Previous estimates of the share of hospitalizations that are avoidable range from 7 to 12 percent for the nonelderly population as a whole and 18 to 28 percent for children.[4] We use the criteria defined in Gadomski et al. (1997), who base their definition on a 1993 Institute of Medicine report on access to health care. The authors revise the general definition provided in the report, excluding adult conditions and dental diagnoses and adjusting the criteria to reflect pediatric illnesses. There are two other definitions used in the literature, but one is not specific to children (Weissman et al, 1992), and the second (Casanova and Starfield, 1995) is a slightly more expansive version of the Gadomski et al. list, classifying 29 percent of the NHDS hospitalizations as avoidable. Given the minimal differences between the two pediatric definitions available, we choose the more conservative measure.

Time series trends in avoidable hospitalizations are presented in Figure 2, which shows both AVH rates per 1,000 population under age 16, and the share of hospitalizations for this age group which are categorized as avoidable. Between 1983 and 1996, there was a steep decline in the AVH rate of nearly 35 percent. However, this decline is slower than the overall decline in hospitalization of children documented above, so the share of hospitalizations that are avoidable is rising.

Previous research on AVHs has concentrated on two areas: (1) calculating age and gender-standardized AVH rates for different populations and types of insurance coverage; (2) establishing a causal link between inadequate ambulatory care and subsequent AVHs. A good example of the research in the first area is Weissman, Gatsonis, and Epstein, who

[4] Weissman et al. (1992); Pappas et al. (1990); Casanova and Starfield (1995); McConnochie et al. (1997a). Note the estimates that include adults exclude psychiatric and obstetrical admissions.

studied the relative risk of admission, by insurance status, for 12 AVH conditions in the under 65 population residing in Maryland and Massachusetts in 1987. After adjusting for age, sex, and baseline hospital utilization for unavoidable conditions, the relative AVH admission rates for the uninsured as compared to the privately insured were 1.71 in Massachusetts and 1.49 in Maryland. For Medicaid recipients, the relative AVH admission rates were 1.84 and 1.65 in Massachusetts and Maryland, respectively.[5]

This work, though useful for descriptive purposes, fails to control adequately for omitted variables influencing both insurance status and AVH incidence, and therefore cannot provide evidence on a potential causal link between the two. For example, those who are uninsured may be in worse underlying health, leading to more avoidable hospitalizations independent of their insurance status. By exploiting exogenous changes in insurance coverage across different age groups and states over time, our approach enables us to surmount these types of biases.

The only previous work of which we are aware that attempts to assess the impact of exogenous insurance shifts on the efficiency of hospitalization is Kaestner, Joyce, and Racine (1999). They use data from 11 states to examine whether children who live in low income areas are less likely to be admitted for avoidable categories of illnesses when Medicaid expands in those areas. Their results are mixed, with decreases in non-asthma avoidable hospitalizations but increases in asthma hospitalizations for younger children, and no impact on older children. One limitation of their approach is that the denominator for their analysis is either total hospitalizations or total births at those hospitals, both of which are likely to be rising as Medicaid expands (since the expansions for pregnancy are correlated with the expansions for children); this could lead to a relative fall in avoidable hospitalizations even as absolute avoidable hospitalizations are rising. The question of relevance for thinking about efficiency is not whether avoidable hospitalizations rose more quickly or slowly than total hospitalizations; it is whether avoidable hospitalizations rise or fall at all as Medicaid expands. This is the question that we address.

[5] Two other studies that examine the relationship between insurance status and AVH rates are Billings and Teicholz (1990) and Pappas et al. (1997).

The remainder of the work in this first area consists of a number of medical papers documenting significantly higher AVH rates among low-income populations and blacks (e.g. Begley et al., 1994; Billings et al., 1993). The authors acknowledge that they cannot fully control for disease prevalence among the different populations, and therefore the evidence they find, while supportive of the hypothesis that AVHs are an outcome associated with poor access to ambulatory care, is not conclusive.

The second strand of literature provides evidence for the presumption that avoidable hospitalizations are indeed avoidable; that is, that increased consumption of outpatient services does, in fact, deliver fewer AVHs. One approach has been to link aggregate measures of access to medical care with corresponding data on AVH rates. Using hospital discharge data from 26 health service areas (HSAs) in Pennsylvania in 1989, Parchman and Culler (1994) find that higher per-capita rates of family and general practice physicians are negatively associated with AVH rates, after controlling for the effects of mean per-capita income. Another approach has been to show that avoidable hospitalizations are associated with inadequate pre-hospital care. Solberg et al. (1990) find that 45% of avoidable hospitalizations studied failed explicit quality criteria and 10% were judged by physicians to have received poor-quality care. A third approach is taken by Homer et al. (1996) and Holfan and Newacheck (1993), who show that places and income groups with lower rates of preventative care for childhood asthma have higher rates of hospitalization, though this association could also be explained by a host of other intermediating factors between location and poverty status and hospitalization. Finally, Gadomski et al. (1998) evaluated the Maryland Access to Care (MAC) Medicaid managed care program, which emphasized improved access to primary care. They find that the program increased the odds of ambulatory care, and that among those children who did use ambulatory care, the program was associated with decreased probabilities of both hospitalization in general and avoidable hospitalization in particular.

Each of these approaches has limitations, but the weight of the evidence supports the contention of a link between inadequate primary care and avoidable hospitalization. We therefore follow the medical literature in employing the AVH rate as a measure of the efficiency of patient care.

2.3 Medicaid Expansions

Historically, Medicaid eligibility for children has been tied to participation in the Aid for Families with Dependent Children program (AFDC). This linkage with AFDC restricted access to the program in three ways. First, despite the existence of the AFDC-Unemployed Parents program (AFDC-UP) which provides benefits to households in which the primary earner is unemployed, AFDC benefits were generally available only to single-parent households. Second, income cutoffs for cash welfare vary across states, and can be very low. For example, in 1984, the cutoff for a family of 4 in South Carolina was only 29 percent of the poverty line. Third, the stigma of applying for cash welfare programs may have prevented eligible families from receiving Medicaid benefits.

In some states, children could also qualify for Medicaid under state Medically Needy or Ribicoff programs. The Medically Needy program relaxed the income criteria for eligibility by covering people who would have been eligible for AFDC if their incomes were lower, but who had large medical expenditures that brought their "net income" below program thresholds. The Ribicoff option allowed states to cover children in two-parent families who met the AFDC income criteria.

Beginning with the Deficit Reduction Act of 1984 (DEFRA '84), the linkage between AFDC coverage and eligibility for Medicaid has gradually been weakened. DEFRA '84 eliminated the family structure requirements for Medicaid eligibility of young children by requiring states to cover children born after September 1, 1983 who lived in families that were income-eligible for AFDC. DEFRA was followed by a series of measures that raised the income cutoffs for Medicaid eligibility, first at state option, and then by federal mandate. These options are described in Appendix 1. The important point to note is that states took up these options at different rates, so that there was a great deal of variation across states in both the income thresholds and the age limits governing Medicaid eligibility.

Over the 1983 to 1996 sample period we use, we estimate that the fraction of children under 16 who were eligible for Medicaid rose by 16 percentage points. But this national

trend masks considerable heterogeneity across the states: there was actually a decline in eligibility of 2% in Alaska during this period, and a rise of 37% in West Virginia. In addition, there is also heterogeneity within states in the rate at which children of different ages were covered. For example, coverage of infants under 1 rose by over 45% in Texas, while coverage of children ages 11 to 15 rose by less than 5%. It is this variation across states, within states over time, and even across different age groups in the same state at a given point in time, that we use to identify our models.

3 Data and Empirical Strategy

3.1 Data

Our study period begins in 1983, nearly a year before the first federally-mandated expansions took effect, and continues through 1996, the latest year for which all the data are available. The source of our hospitalization data is the National Hospital Discharge Survey (NHDS), the only continuous nationwide survey of inpatient utilization of non-federal, short-stay hospitals. The NHDS samples approximately 250,000 discharges annually, collecting data on diagnosis and procedure codes, discharge status, length of stay, and selected hospital and demographic characteristics. Weights provided with the survey data enable estimation of statistics for the universe of annual hospitalizations in the United States.

Because our primary independent variable of interest, Medicaid eligibility, varies only by state, birth date, and calendar quarter, we group the individual hospital data into cells. The sample size does not permit grouping at such a fine level of detail, so we define cells for 4 age categories for each state and year. The age categories are children under 1 year old, 1-5 year-olds, 6-10 year-olds, and 11-15 year-olds. Note that the under 1 category does not include the initial hospitalization of newborns admitted upon birth. This age group nevertheless warrants its own category, both because it accounts for 27.6% of total hospitalizations to children under 15 during the study period, and because many federal

and state initiatives have expanded Medicaid eligibility specifically for infants under 1 year old.

Of the resulting 2,856 cells (4 age categories * 14 years * 51 "states" (50 states plus Washington, DC), we drop 348 because the corresponding state-years are not surveyed at all, 180 because they are poorly surveyed for several consecutive years, and 20 because they are undersampled in advance of being excluded entirely from the sample. These rules affect 16 states in total: 3 are dropped entirely from the sample, 11 are dropped in the late 1980s when the survey data suddenly becomes patchy or disappears, and 2 are missing data for 2 consecutive years in the middle of the study period but are otherwise included in the sample. Regressions of a dummy for inclusion in the data set on our independent variables revealed no systematic relationship between the probability of inclusion and our variables of interest. Each of the remaining 2,308 cells is then matched to the appropriate age/state/year population estimate from the Census Bureau. We calculate hospitalization rates by dividing the weighted number of hospitalizations in each cell by population.

The major advantage of the NHDS is that it provides a large, nationally representative sample of hospital discharges, with information on diagnosis at hospitalization that can be used to identify avoidable hospitalizations. The major disadvantage is that the NHDS is not designed to yield state-specific estimates of either total or child hospitalizations. Discharges from hospitals with 1,000 or more beds are sampled with certainty, while discharges from smaller institutions are selected using a stratified, three-stage design, with selection of primary sampling units (PSUs), hospitals within the selected PSUs, and discharges within the hospitals constituting the first, second, and third stages, respectively.

This sampling design leads to two problems for the empirical analysis, which relies on state level estimates of hospitalization rates. First, this sampling approach can and does leave a number of states entirely (or almost entirely) out of the survey. Discharges in the states that are included in the survey are overweighted in order to produce national estimates; thus, a number of state cells have large numbers of weighted hospitalizations relative to the underlying state population. Since we only include states that have survey data, this results in a high rate of hospitalizations in our dataset, relative to the true

national average. Second, since the PSUs can cross state boundaries, a sample which is representative of a PSU need not represent the individual states that comprise it.

Neither of these factors would present a significant problem for the analysis if the sampling rules remained fixed from year to year. By including state fixed effects, we can capture the extent to which states' estimated hospitalization rates deviate from representative levels. We can also reduce the influence of outliers by censoring the hospitalization rates.[6] But there is reason to believe that the sampling rules within states change over time, particularly in 1987 when there is a redesign of the NHDS. This could be particularly problematic for our analysis if there is a shift in the composition of hospitals across states within a PSU.

As a result, we also include in our model a set of state*year interactions. These interactions allow for changes within states over time in the sampling frame of hospitals, and also control for other state time trends which may be correlated with Medicaid eligibility policy. Our model is still identified when these are included, since the expansions occurred at a differential pace for different age groups.

The final issue related to the sampling design concerns the question of what weights to use for our regression analysis. The accuracy of the NHDS estimate for a given cell depends not on the sample size of that cell per se, but on the sampling probability of a discharge within that cell. Thus, even if a larger number of discharges for 1-5 year-olds are sampled in California than in Rhode Island, the accuracy of the hospital statistics for 1-5 year-olds in Rhode Island will be much greater if the sample represents a larger fraction of the universe of discharges. Restrictions on the use of our NHDS dataset, discussed briefly below, prevented our calculating these sampling probabilities for each cell. We were, however, able to develop approximate sampling probabilities for each state and year using the ratio of total NHDS survey discharges in that state and year to total discharges in that state and year as reported by the American Hospital Association.

Descriptive statistics for our cell data, calculated using these weights, are presented in Table 3. The first panel shows several key variables as a fraction of the population. The

[6] We censor the individual cell hospitalization rate at 0.5. Our results are not very sensitive to the censoring point used.

hospitalization rate in our sample is 10.3%, which is significantly higher than the aggregate rate shown in Figure 1; as noted above, this arises through the fact that we are only using sampled cells in the NHDS, which are overweighted to represent the nation. Nevertheless, the time trend in our data is very similar to the national trend, suggesting little systematic bias to our estimates as a result. The AVH rate is 2.5 percentage points, or 24% of the total hospitalization rate. The incidence of the leading causes of avoidable hospitalization are shown as well. The second panel describes the distribution of characteristics of hospitalizations. About 56% of hospitalizations are financed by private insurance, and about one-quarter by Medicaid. Over four-fifths of hospitalizations in the sample occur in non-profit hospitals.

Due to the sensitive nature of the information gathered in the NHDS, geographic identifiers are not released in the public use files. We were able to create the NHDS data cells and match Medicaid policy variables to those cells through an agreement with the Research Data Center at the National Center for Health Statistics. Once the dataset was complete, we were allowed restricted remote access to the data.

3.2 Empirical Strategy

Our key variable of interest is the percentage of children in each age group, state, and year eligible for Medicaid. We estimate this variable using a detailed simulation model originally developed for Currie and Gruber (1996a,b), and updated through 1996 for this project. This model uses information on family structure, age, income, state and year to impute eligibility for Medicaid using state-specific rules for AFDC and expansion eligibility. These earlier papers describe this model in more detail.

We begin by extracting data for 0 to 16 year-olds from the March Current Population Survey (CPS) data for each year, which has sufficient information on income, family structure, and location to determine eligibility for Medicaid. We then compute eligibility for each child in the CPS data, aggregate into the age groups used for our NHDS sample (0, 1-5, 6-10, 11-15), and match the eligibility measures onto the NHDS sample by age group, state, and year.

After matching these eligibility measures to our NHDS data, we can estimate models of the following form:

$$(1)\ HOSP_{ajt} = \alpha + \beta_1 ELIG_{ajt} + \beta_2 \eta_a + \beta_3 \delta_j + \beta_4 \tau_t + \beta_5 \delta_j \tau_t + \varepsilon_{ajt}$$

where a indexes age groups, j indexes states, and t indexes years; HOSP is the hospitalization rate (or one of our other dependent variables), ELIG is the fraction of children eligible for Medicaid in each age group/state/year cell, and η_a, δ_j, and τ_t are full sets of dummy variables for age group, state, and year, respectively.

This model relates the rate of hospitalization in a cell to the probability that a child in that cell is eligible for Medicaid. We control for age group, state, and year fixed effects to capture any underlying correlation between Medicaid eligibility and hospitalization across these groups. In addition, as discussed above, we include a full set of state*year interactions to control both for any changes in the NHDS sampling frame that change how a state is represented in our data, and for other state-specific trends that might be correlated with Medicaid eligibility policy.

Even in this rich framework, however, two concerns remain with our ELIG measure. The first is measurement error: given the small sample sizes by age group and state in the CPS, there is likely to be substantial noise in our measure relative to true population Medicaid eligibility. The second is omitted variables bias: the actual eligibility of these children will be correlated with omitted factors that also determine their hospitalization rates. For example, a recession that hits a given state/age group particularly hard may lead to both rising Medicaid eligibility and rising hospitalization.

We therefore instrument for actual eligibility using what Currie and Gruber call "simulated eligibility". To construct this instrument, we begin by drawing a nationally representative random sample of 250 children of each age from each year's CPS. Then, we take this *same sample* through our simulation programs to calculate the fraction of children of each age who would be eligible for Medicaid if they lived in each state. That is, we ask how many zero year olds would have been eligible had they lived in California, how many would have been eligible had they lived in Texas, etc. We then once again aggregate these

data into the NHDS age groupings, and match them onto the NHDS data by age group, state and year. These simulated eligibility estimates become instruments for actual eligibility, and we estimate our models below by two-stage least squares.

This nationally representative population measure provides a convenient index of the generosity of state Medicaid rules that utilizes only variation in the eligibility rules across states, years, and age groups of children. It is independent of factors specific to state/age groups that might affect both Medicaid eligibility and hospitalization rates. This instrumental variables strategy also surmounts measurement error problems in our actual eligibility measure, so long as the error does not derive from miscoding of state rules. As shown in Table 3, about one-quarter of the children for whom hospital data is available are estimated to be eligible for Medicaid over this sample period.

4 Basic Results

4.1 Total Hospitalizations

The first column of Table 4 presents our results for total hospitalizations. As noted above, our dependent variable is the rate of hospitalizations per child, and our independent variable of interest is the percentage of children in that age group/state/year cell eligible for Medicaid. We show only the coefficient of interest from models that also include a full set of age group, state, and year dummies, as well as state*year interactions.

Our first important finding is that increases in Medicaid eligibility are associated with increases in hospitalizations. We estimate that for each percentage point of children made eligible for Medicaid, hospitalizations rise by 0.066 percentage points. That is, we estimate that if all children were made eligible, hospitalizations would rise by 6.6 percentage points, or by 64% of their baseline value. Since the expansions over our time period increased eligibility by 16 percentage points, we estimate that they increased child hospitalization by 1.06 percentage point, or 10.3 percent.

This finding confirms Currie and Gruber's (1996b) finding that children are more likely to be hospitalized if they are Medicaid-eligible. Our estimate is somewhat smaller than theirs; they found that making a child eligible for Medicaid doubled the odds of hospitalization. But their analysis examines the odds of a child experiencing at least one hospitalization, whereas our examines total hospitalizations per capita. If Medicaid serves to increase first hospitalizations of children, but to reduce additional hospitalizations, the two results are readily reconciled.

This finding also reveals that, if the Medicaid expansions did increase the efficiency of care, this effect was not large enough to produce a decline in total hospitalizations. That is, either efficiency did not rise, or any efficiency gains were offset by increased access of children for unavoidable inpatient care. We return to this point below.

4.2 Avoidable Hospitalizations

The next column of Table 4 shows our findings for avoidable hospitalizations per capita. In fact, we find a very significant negative effect of Medicaid eligibility on avoidable hospitalizations. Our estimates suggest that for each percentage point increase in eligibility, avoidable hospitalizations fall by 0.034 percentage points. That is, an out-of-sample extrapolation suggests that if all children were Medicaid-eligible, there would be no avoidable hospitalization. More relevantly, we find that the expansions over the 1983-1996 period reduced avoidable hospitalizations by 0.54 percentage points, or 22%.

This striking finding suggests substantial efficiency gains to providing public insurance coverage to children. We cannot prove through this evidence that the route to more efficient hospital care was improved use of ambulatory care. But, given the nature of these types of admissions, and given that Currie and Gruber (1996b) find significant improvements in access to primary care associated with the Medicaid expansions, this result certainly implies that improved ambulatory care is the cause of increased efficiency of hospitalizations.

To gain a clearer picture of how Medicaid impacts avoidable hospitalizations, in Table 5 we consider separately the impact of Medicaid eligibility on each of the six most frequent

categories of avoidable hospitalizations: asthma; pneumonia; gastroenteritis; ear, nose, and throat (ENT) infections; kidney/urinary tract infections; and dehydration.

Our results here are quite interesting. For four of the six top conditions, the impact of Medicaid is negative, and it is significant for pneumonia, gastroenteritis, and ENT infections. For kidney/urinary tract infections, the coefficient is positive, but not significant. But for dehydration, the coefficient is positive and significant. This is striking since the type of ambulatory care that is likely to be most effective in preventing dehydration is not preventive care, but rather emergent ambulatory care. This suggests that for the conditions for which preventive care is most key, there is very strong support for a causal role of Medicaid in reducing avoidable hospitalization.

4.3 Reconciling the Hospitalization Results

Our finding that the Medicaid expansions simultaneously decreased the avoidable hospitalization rate by approximately 0.54 percentage points and increased the total hospitalization rate by 1.06 percentage points implies that "unavoidable" hospitalizations rose by 1.6 percentage points, or 16% of our baseline hospitalization rate. That is, the access gains of expanded Medicaid eligibility were quite large. This finding begs the question: what kind of hospitalizations were so responsive to the increase in insurance coverage?

In fact, as noted earlier, there is a substantial literature on child hospitalization which suggests that a large share of hospitalizations are for "discretionary" diagnoses that may respond to insurance coverage. "Discretionary" admissions involve a substantial amount of physician discretion, and can often be handled on an outpatient basis. They are also characterized by a lack of clinical consensus regarding the appropriate course of treatment, and large locational variation in admit rates. A study of hospital records in four states in the early 1980s finds that 14 to 22 percent of all admissions for all age groups occurred in the "most discretionary" DRG codes, defined using measures of local variation in admit rates (Roos et al. 1988). A more recent study (McConnochie et al.1997b) of geographic variation in rates of infant hospitalization in Rochester, New York reveals that 59 percent

of hospitalizations were discretionary, as compared to 18 percent that were mandatory (defined as a diagnosis "for an acute condition that is life-threatening or has the potential to produce long-term disability without (or even with) immediate hospitalization").

It is difficult to assess directly the impact of the Medicaid expansions on discretionary hospitalizations, since the sole compilation of diagnoses that we can find is designed for infants only. However, as a specification check that our results are sensible, we can assess whether our finding of an increase in total hospitalizations is reflected in a category of mandatory hospitalization that seems unlikely to respond to Medicaid eligibility: the hospitalization rate for severe fractures, burns, and trauma. That is, if our finding of rising total hospitalizations reflects not rising discretionary admissions, but rather some spurious omitted variable, then we should see rises in mandatory admissions as well. But if the mechanism is the one that we suggest, then such mandatory admissions should not be rising with eligibility increases.

In fact, we find no significant relationship between the hospitalization rate in this category and Medicaid eligibility. The coefficient of Medicaid eligibility in a regression using the hospitalization rate for severe fractures, burns, and trauma as the dependent variable is -0.0002 (.0011). This falsification exercise provides support for our hypothesis that the Medicaid expansions led to a greater number of unavoidable, discretionary admissions.

4.4 Implications

Assessing the implications of these findings is difficult. In principle, the efficiency gains from reduced avoidable hospitalizations may be quite large. Among children enrolled in Medicaid in 1996, average hospital expenditures per year per user of hospital services was $3,627 (U.S. Department of Health and Human Services, 1998). The typical user of hospital services has 1.5 inpatient stays per year (Hahn, 1992), so that the cost per stay was approximately $2,418. While data is not specifically available on the cost of an avoidable hospitalization, lengths of stay for avoidable hospitalizations are on average about 2/3 those for unavoidable hospitalizations, so that we can roughly impute their cost

as $1600. This is roughly forty times the mean cost of an ambulatory visit per user of ambulatory services, once again corrected for the frequency of service use. Thus, so long as the ambulatory care that reduced the incidence of avoidable hospitalizations consisted of fewer than 40 episodes, there were cost savings from these increases in how care was delivered.

Of course, not only those children who are at risk for avoidable hospitalization will increase their usage of primary care, so that even if for a given child there were fewer than 40 additional primary care visits associated with an avoided hospital stay, over all children the Medicaid expansions may have been associated with more than 40 additional visits per avoided hospitalization. However, the available evidence suggests that there were fewer than 40 increased visits per hospitalization avoided. Currie and Gruber (1996b) find that making a child eligible for Medicaid lowers the odds of going a year without a physician visit by 10 percent. We find here that if all children were eligible for Medicaid the rate of avoidable hospitalization per capita would fall by 3.4%. This suggests that there are only on the order of three increased visits per hospitalization avoided. Of course, the 10% figure is a lower bound, since Medicaid would increase not just the odds of seeing a physician, but the frequency with which a physician is seen. Moreover, it may be that the physician contacts that allow children to avoid hospitalization are more expensive than average. But even if the rate of physician contacts rose substantially, and even if they were somewhat more costly than average, it seems unlikely that this calculation would approach the point where the increased ambulatory care was not cost-effective.

At the same time, however, Medicaid is associated with an even larger rise in unavoidable, discretionary hospitalizations. As a result, the expansions are raising total costs. Evaluating the costs and benefits of these increased hospitalizations is very difficult, and relies critically on the value of any health improvements to children from increased access to the hospital. Currie and Gruber (1996b) document that the Medicaid expansions overall were associated with a significant decline in child mortality, but there is no way to decompose from their estimates the share of these health improvements that are due to hospital access.

In summary, it seems likely that the reduction in avoidable hospitalization that we document was due to efficiency gains from increased primary care. Whether the increase in total hospitalizations due to the Medicaid expansions was cost-effective, in terms of cost per unit of health improvement, is unclear.

5 Impact of Medicaid on the Nature of Child Hospitalization

Our analysis thus far has focused on the use of hospital data to provide a marker for trends in the efficiency with which medical care is delivered. But there are a separate set of interesting issues associated with how expansions in public insurance impact the general nature of child hospitalization. How does public insurance eligibility expansion affect the insurance coverage of those who are hospitalized? How does it impact the intensity with which children are treated in the hospital? How does it impact where children are treated?

5.1 Insurance Coverage of Hospitalized Children

Expansions of Medicaid eligibility can have both direct and indirect effects on the insurance coverage of hospitalized children. The direct effect is to increase the number of hospitalizations that are paid for by Medicaid. The magnitude of this direct effect will be the product of two factors: the marginal takeup rate of Medicaid by the newly eligible; and the rate at which those newly eligible are hospitalized. There is considerable evidence on the first of these factors which suggests fairly low marginal takeup rates, on the order of 25% (Currie and Gruber, 1996b; Cutler and Gruber, 1996). There is little evidence on the second. Moreover, these two factors interact, as much of the takeup decision for hospital treatment is made not by the individual but by the hospital; in the wake of Medicaid expansions, hospitals have set up extensive facilities for enrolling eligible uninsured patients in Medicaid (US GAO, 1994).

The indirect effect of the Medicaid expansions may be to lower the coverage of hospitalizations of children by private insurance. This could occur through the "crowdout" mechanism introduced by Cutler and Gruber (1996). Since privately insured individuals

must pay, on average, roughly two-thirds of the cost of their medical care, some of them may switch to the free public insurance provided by Medicaid when they become eligible. Cutler and Gruber estimate quite large crowdout, with one of every two persons enrolling in Medicaid formerly having private insurance; this reduction in private insurance amounts to about 20% of the privately insured who were made eligible by the expansions. Subsequent work has produced a wide range of estimates, with a number of studies confirming large crowdout effects (e.g. Shore-Sheppard, forthcoming; Currie, 1996) and a number disputing that the effects are sizeable (e.g. Dubay and Kenney, 1997; Blumberg, forthcoming). Once again, the magnitude of this effect would be the product of the extent of crowdout, and the extent to which crowded out children are hospitalized. The latter might be expected to be well below the average rate of hospitalization of privately insured children, as parents may be willing to substitute lower quality Medicaid coverage for higher quality private coverage only when their children are unlikely to need medical care.

The impacts of the expansions on the insurance coverage of those hospitalized are shown in Table 6. The dependent variable here is total hospitalizations covered by different payers, relative to population. We find that the expansions were associated with more hospitalizations paid for by Medicaid; each percentage point of eligibility is associated with a 0.057 percentage point increase in Medicaid-financed hospitalizations. This figure is much lower than the marginal takeup rates discussed earlier, but this is not surprising since it is also multiplied by hospitalization rates. Indeed, since the average hospitalization rate in our sample is 10.3 percent, if those taking up were hospitalized at the average rate we would have expected a coefficient of only 0.026. The fact that the coefficient is more than twice this figure suggests that those taking up are hospitalized at much higher than average rates.

In the second column, we show that hospitalizations financed by private insurance actually appear to increase as Medicaid expands, contradicting the crowdout hypothesis, but that the coefficient is insignificant and small. It is unclear why higher Medicaid eligibility would be associated with a rise in privately financed hospitalizations. But, given the small size and insignificance of this coefficient, the general conclusion appears to be that there is little evidence of crowdout operating here. This could be consistent with small

crowdout on average; alternatively, there could be substantial crowdout on average, but low crowdout among those privately insured families whose children are likely to be hospitalized (since those families are the ones least likely to move to the public system).

The third column shows the impact on uninsured hospitalizations, which fall significantly. Thus, the expansions of Medicaid appear to be associated with a substantial shift in hospitalizations that are not insured to hospitalizations that are financed by the Medicaid program. The smaller magnitude of the coefficient in the uninsured regression relative to the Medicaid regression reflects the fact that inpatient utilization increases with Medicaid coverage. Not only are those hospitalizations that were formerly uninsured now being financed by Medicaid, but the newly eligible are going to the hospital more often.

5.2 Intensity of Treatment

An issue that has received considerable study in the health literature is whether insurance status differentials are associated with differences in the intensity of treatment of patients in the hospital. A large literature, reviewed in Weissman and Epstein (1990) and in Currie and Gruber (1999), has compared the treatment of groups with different types of insurance coverage and reached somewhat mixed conclusions: those with private insurance coverage are treated much more intensively than are the uninsured, but those with public insurance coverage do not appear to be consistently treated more intensively. Currie and Gruber (1999) extend this literature by examining the impact of the Medicaid expansions on the intensity of treatment of childbirth. They find no aggregate impact on intensity of treatment, but they do find an important compositional impact. For those mothers who were likely to be uninsured prior to becoming Medicaid-eligible, there was a significant increase in treatment intensity. On the other hand, for those mothers who were likely to be privately insured, and therefore subject potentially to crowdout, treatment intensity decreased. This is a logical result of the fact that Medicaid reimburses providers at much lower levels than does private insurance, so that a move from private to Medicaid coverage would lower incentives for intensive treatment.

We examine the impact of Medicaid on the intensity with which children are treated in the hospital. We follow the literature on the hospitalization of the elderly to consider two dependent variables: length of stay in the hospital, in days; and the number of procedures performed on the child (Cutler, 1991). Since over 50% of our sample has no procedures performed on them during their stay in the hospital, we also consider a dummy variable for having an inpatient procedure.

For this analysis, we are considering average treatment of those in the hospital; thus, we are not comparing hospitalization figures to underlying population rates, but rather considering the impact of the expansions on the nature of how those who are hospitalized are treated. Doing so runs into a critical difficulty of interpretation because the Medicaid expansions are affecting the mix of who is hospitalized. Thus, the expansions will have compositional impacts, in addition to supply-side impacts, on the nature of hospitalizations. The compositional changes have an uncertain effect on our coefficients. On the one hand, avoidable hospitalizations are falling; since these hospitalizations are treated less intensively on average, the Medicaid expansions will be associated with a higher level of intensity of the remaining hospitalizations through compositional effects. On the other hand, however, unavoidable hospitalizations are rising even more than avoidable hospitalizations are falling, and the marginal unavoidable hospitalization for a new Medicaid enrollee may have a lower intensity of treatment. This would lead the expansions to be associated with a lower level of intensity through compositional effects.

The direct supply-side incentives have uncertain effects as well, as there will be more intensive treatment of those moving from an uninsured state to Medicaid, but less intensive treatment of those moving from private insurance to Medicaid. Thus, the prediction for treatment intensity is quite ambiguous. Of course, this discussion does not necessarily mitigate the interest of these types of results. It is still important in a reduced form sense to understand what public insurance coverage does to the nature of hospitalization. But we cannot attach any structural interpretation to our findings in terms of conditional impacts on treatment or other features of the data; public insurance may be affecting intensity for either supply incentive or composition reasons.

Our results are shown in Table 7. Perhaps for the reasons just described, we find very mixed evidence on treatment intensity. We find a significant increase in both the number of procedures and the odds of having any procedure; we estimate that a one percentage point increase in eligibility raises the odds of having a procedure by 0.3 percentage points, or 0.63 percent of baseline. At the same time, however, there is a significant and sizeable decline in length of stay, suggesting that each percentage point increase in Medicaid eligibility lowers the length of stay by 0.011 days, or 0.25 percent of baseline. Thus, the Medicaid expansions appear to be leading to shorter stays for children in the hospital on average, but more intensive treatment per day when hospitalized.

5.3 Types of Hospitals

Another interesting aspect of hospitalization that might be affected by the expansions is the type of hospital to which children are admitted. If non-government hospitals have structures in place to reduce their accessibility to the uninsured, then expanding Medicaid may increase access of low-income populations to these types of hospitals. In particular, given the relatively generous levels of Medicaid reimbursement to hospitals in the world of managed care in the private sector, hospitals may be eager to solicit the business of formerly uninsured patients who become insured by Medicaid.

In the next panel of Table 7, we consider the impact of Medicaid expansions on the type of hospitals to which children are admitted; the dependent variables are the share of hospitalizations in different hospital ownership categories. In fact, we find a very strong impact of the expansions on where children are hospitalized: there is an equal and opposite reduction in government hospitalizations and rise in for-profit hospitalizations, of about 0.055 percentage points for each percentage point increase in Medicaid eligibility. At these estimates, a 100% level of Medicaid eligibility would double the share of children admitted to for-profit hospitals, and almost halve the share admitted to government hospitals. There was no impact on admits to non-profit hospitals.

These findings suggest that different types of hospitals do care about insurance coverage in deciding who to admit, particularly for the types of discretionary admissions that are

making up a large share of the hospitalizations of children in our sample (as opposed to emergency admissions, where hospitals are legally bound to treat all who arrive at the emergency room). When children are entitled to Medicaid coverage, they are made more attractive to for-profit hospitals, who pull them from the public hospitals in which they were treated as uninsured patients.

6 Conclusions

The relentless rise in the number of uninsured in the U.S. ensures that public insurance policy will remain a topic of considerable interest for the near term. Moreover, whenever the advantages of public insurance are discussed, enhanced efficiency of care is always listed as one of the major benefits of insuring more of our nation's citizens, and in particular more children. But there is little evidence to suggest directly that providing public insurance increases the efficiency with which care is delivered, as opposed to simply providing more care.

We provide such evidence. We find that over the 1983-1996 period, expansions in the Medicaid program significantly increased the rate at which children were hospitalized, with the expansions raising hospitalization rates of children by 10%. But we also find that hospitalizations objectively classified as avoidable by medical experts fell sharply, with the expansions inducing a 22% reduction. This suggests that public insurance can improve the efficiency of care, and substantially reduce the share of hospitalizations that are avoidable, while at the same time expanding overall access of low-income populations to hospital care.

We then turned to the implications of the expansions more generally for child hospitalization. We found that the post-expansion world was one with more hospitalizations financed by Medicaid, more intensive treatment per hospital day but fewer days in the hospital, and a shift from public to for-profit hospitalization.

Our findings, taken together with other evidence on the Medicaid expansions, suggest that increased public insurance eligibility for low-income families has led to both improved health and more efficient use of medical care. A central question for policy-makers is whether this is likely to continue to be the case as insurance eligibility is extended further

up the income scale. Higher- income individuals who gain insurance coverage through Medicaid may have obtained better ambulatory care before becoming eligible, mitigating any efficiency increases through Medicaid. An important question for future research is to evaluate how the efficiency of care evolves as higher-income children become eligible under the CHIP program recently enacted by Congress.

Table 1. Top Hospital Diagnoses and Prevalence by Age Category, 1996

	Number (000s)	% of total
Under 15		
Diseases of the respiratory system	653	30%
Injury and poisoning	223	10%
Diseases of the digestive system	205	9%
Endocrine, nutritional and metabolic diseases, and immunity disorders	155	7%
Infectious and parasitic diseases	153	7%
All diagnoses	**2,207**	**100%**
15-64		
Deliveries	3,817	23%
Diseases of the circulatory system	2,119	13%
Mental disorders	1,546	9%
Diseases of the digestive system	1,503	9%
Injury and poisoning	1,350	8%
All diagnoses	**16,619**	**100%**
65 plus		
Diseases of the circulatory system	3,963	34%
Diseases of the respiratory system	1,550	13%
Diseases of the digestive system	1,198	10%
Injury and poisoning	977	8%
Neoplasms	826	7%
All diagnoses	**11,718**	**100%**
All diagnoses, all ages	**30,544**	

Notes: National Center for Health Statistics (1998).

Table 2. Pediatric Avoidable Hospitalization Conditions

Condition	ICD-9-CM Code(s)	Qualifiers
Immunization preventable conditions	033, 037, 045, 320.0, 390, 391	Haemophilus meningitis (320.2) for age 1-5 only
Grand Mal status and other epileptic convulsions	345	Age 0-5 years
Convulsions "A"	780.3	Age > 5 years
Convulsions "B"	780.3	
Severe ENT infections	382, 462, 463, 465, 472.1	Exclude otitis media (382) with myringotomy with insertion of tube (procedure 20.01)
Bacterial pneumonia	481, 482.2, 482.3, 482.9, 483, 485, 486	Exclude cases with secondary diagnosis of sickle cell (282.6) and patients < 2 months
Asthma	493	
Tuberculosis	011-018	
Cellulitis	681, 682, 683, 686	Exclude cases with a surgical procedure (01-86.99)
Diabetes "A"	250.1, 250.2, 250.3	
Diabetes "B"	250.8, 250.9	
Diabetes "C"	250.0	
Hypoglycemia	251.2	
Gastroenteritis	558.9	
Kidney/urinary infection	590, 599.0, 599.9	
Dehydration-volume depletion	276.5	
Iron deficiency anemia	280.1, 280.8, 280.9	Age 0-5 years
Nutritional deficiencies	260, 261, 262, 268.0, 268.1	
Failure to thrive	783.4	Age < 1 year

Source: Gadomski et al. (1998)

Table 3. Descriptive Statistics

	Mean	Std. Deviation
NHDS		
Statistics for Total Population (N = 3,208)		
Hospitalization Rate		
Overall	10.25%	1.08%
Medicaid	3.07%	0.47%
Private insurance	5.41%	0.62%
Uninsured	0.95%	0.28%
Other/unknown	1.45%	0.41%
AVH rate		
Overall	2.48%	0.32%
Asthma	0.44%	0.06%
Pneumonia	0.52%	0.09%
Gastroenteritis	0.41%	0.09%
ENT infections	0.42%	0.09%
Kidney/Urinary Tract Infections	0.13%	0.03%
Dehydration	0.25%	0.07%
Statistics for Hospitalizations (N = 3,206)		
AVH share	24.93%	1.33%
Share by Race		
Black	14.59%	1.59%
White	62.13%	2.41%
Other	7.03%	1.36%
Unknown	16.25%	2.20%
Share by Payer		
Medicaid	25.27%	1.37%
Private insurance	56.19%	1.71%
Uninsured	7.40%	0.62%
Other/unknown	11.14%	1.35%
Share by Hospital Ownership		
For profit	4.94%	1.12%
Not for profit	81.27%	2.41%
Government	13.80%	2.01%
Average LOS	4.27	0.16
Fraction with procedures	47.68%	1.80%
Average number of procedures	0.81	0.04
CPS (N = 3,208)		
ELIG	23.37%	1.45%
SIMELIG	24.21%	1.28%

Table 4. Basic Results For Total and Avoidable Hospitalizations (N=2,308)

	Total Hospitalizations/Pop	Avoidable Hospitalizations/Pop
Medicaid Eligibility	0.066 (0.026)	-0.034 (0.010)
Mean of Dependent Variable	0.103	0.025

Notes: Coefficient is that on Medicaid eligibility from estimating regressions such as (1) in the text, using SIMELIG as an instrument for ELIG. Fixed effects for age group, state, and year, as well as state*year interactions are also included. Standard errors are in parentheses.

Table 5. Specific Avoidable Conditions (N=2,308)

Condition	Medicaid Eligibility Coefficient	Mean
Pneumonia	-0.0106 (0.0035)	0.0052
Asthma	-0.0016 (0.0026)	0.0044
ENT Infections	-0.0152 (0.0033)	0.0042
Gastroenteritis	-0.0175 (0.0037)	0.0041
Dehydration	0.0127 (0.0028)	0.0025
Kidney/Urinary Tract Infections	0.0013 (0.0014)	0.0013

Notes: Coefficient is that on Medicaid eligibility from estimating regressions such as (1) in the text, using SIMELIG as an instrument for ELIG. Fixed effects for age group, state, and year, as well as state*year interactions are also included.

Table 6. Insurance Coverage (N=2,308)

	Medicaid Covered	Privately Insured	Uninsured
Medicaid Eligibility	.057	.011	-.032
	(.015)	(.019)	(.011)
Mean of Dependent Variable	.031	.054	.009

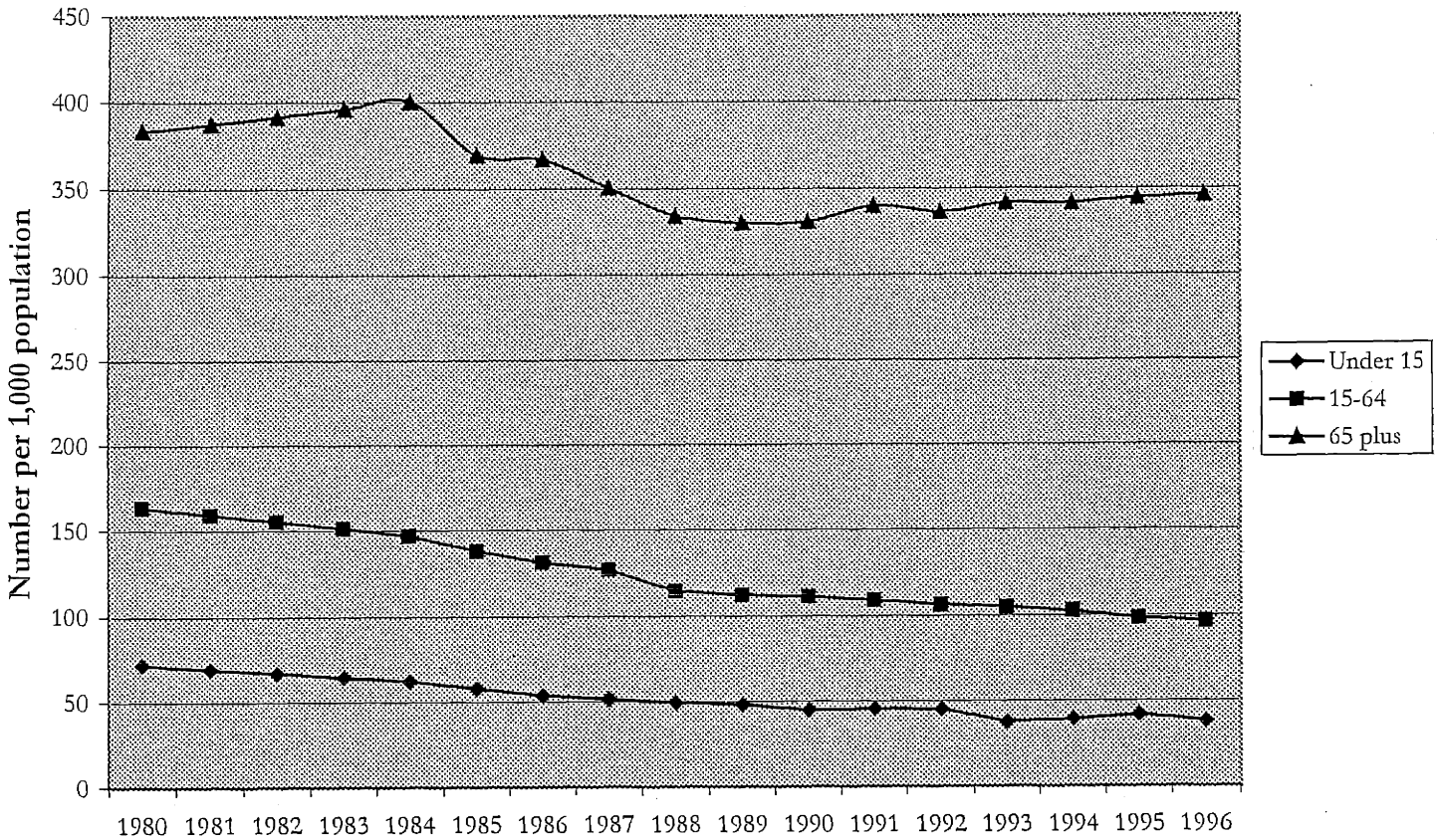
Notes: Coefficient is that on Medicaid eligibility from estimating regressions such as (1) in the text, using SIMELIG as an instrument for ELIG. Fixed effects for age group, state, and year, as well as state*year interactions are also included.

Table 7. Treatment and Type of Hospital (N=2,306)

	Medicaid Eligibility Coefficient	Mean of Dependent Variable
Treatment		
Length of Stay	-1.082	
	(.640)	4.27
Number of Procedures	.375	.811
	(.107)	
Any Procedures	.300	
	(.045)	.476
Type of Hospital		
For-Profit Hospital	.056	
	(.025)	.049
Non-Profit Hospital	-.003	
	(.032)	.813
Public Hospital	-.053	
	(.028)	.138

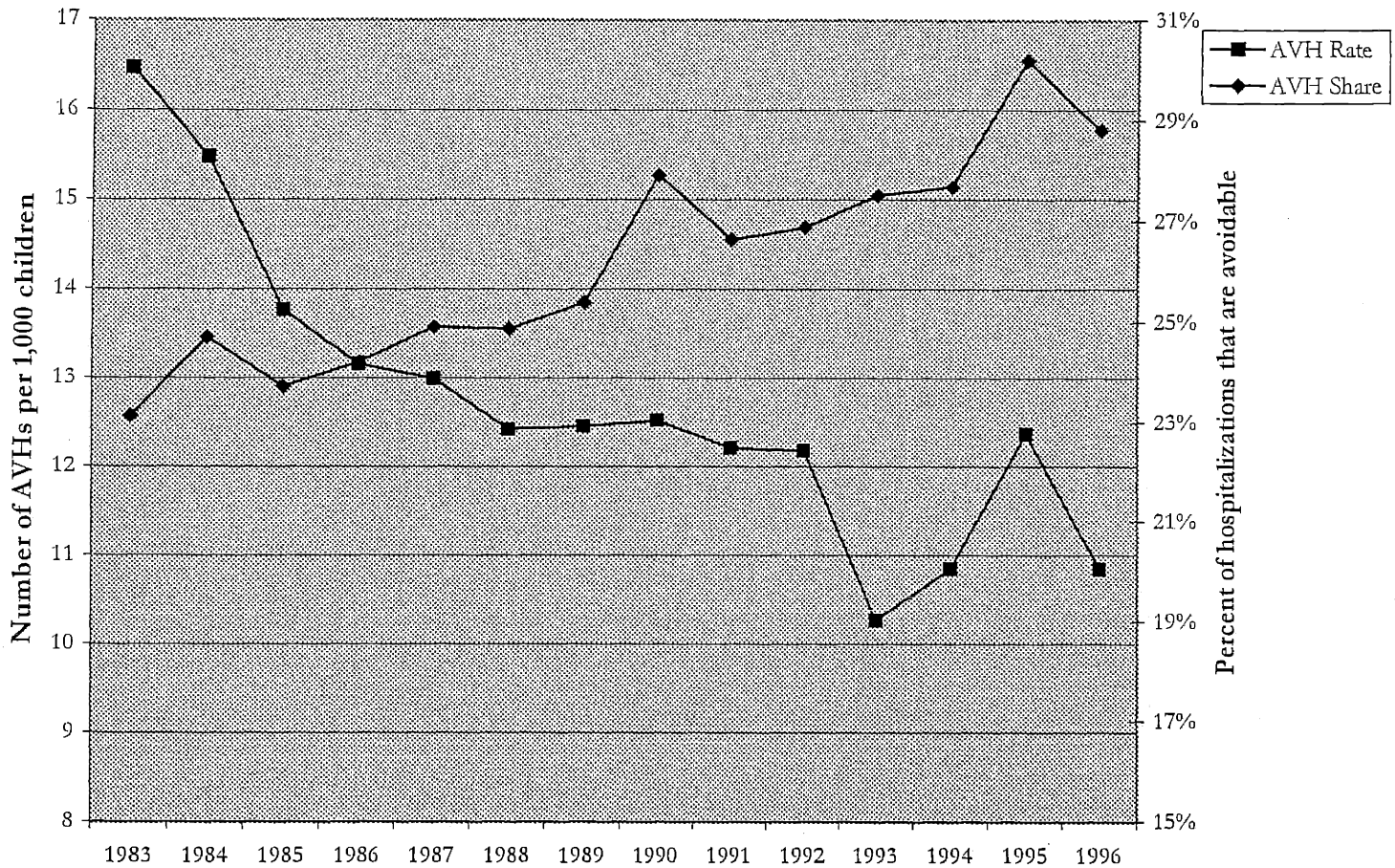
Notes: Coefficient is that on Medicaid eligibility from estimating regressions such as (1) in the text, using SIMELIG as an instrument for ELIG. Fixed effects for age group, state, and year, as well as state*year interactions are also included.

Figure 1. Hospitalization Rates by Age Group



Source: National Center for Health Statistics (various years)

Figure 2. Avoidable Hospitalizations of Children Under 16, 1983-1996



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Appendix : The Medicaid Expansions

Deficit Reconciliation Act, 1984: Effective October 1, 1984. Required states to extend Medicaid coverage to children born after September 30, 1983, if those children lived in families that were income-eligible for AFDC.

Omnibus Budget Reconciliation Act, 1986: Effective April 1, 1987. Permitted states to extend Medicaid coverage to children in families with incomes below the federal poverty level. Beginning in fiscal year 1988, states could increase the age cutoff by one year each year, until all children under age five were covered.

Omnibus Budget Reconciliation Act, 1987: Effective July 1, 1988. Permitted states to cover children under age 2, 3, 4, or 5, who were born after September 30, 1983. Effective October 1, 1988, states could expand coverage to children under age 8 born after September 30, 1983. Allows states to extend Medicaid eligibility to infants up to one year of age in families with incomes up to 185 percent of the federal poverty level. States were required to cover children through age 5 in fiscal year 1989, and through age 6 in fiscal year 1990, if the families met AFDC income standards.

Medicare Catastrophic Coverage Act, 1988: Effective July 1, 1989, states were required to cover infants up to age on in families with incomes less than 75 percent of the federal poverty level. Effective July 1, 1990, the income threshold was raised to 100 percent of poverty.

Family Support Act, 1988: Effective April 1, 1990. States were required to continue Medicaid coverage for 12 months among families who had received AFDC in three of the previous six months, but who had become ineligible because of earnings.

Omnibus Budget Reconciliation Act, 1989: Effective April 1, 1990. Required states to extend Medicaid eligibility to children up to age 6 with family incomes up to 133 percent of the federal poverty line.

Omnibus Budget Reconciliation Act, 1990: Effective July 1, 1991. States were required to cover all children under age 19 who were born after September 30, 1983 and whose family incomes were below 100 percent of the Federal poverty level.

Hospital Responses to Changes in Average Reimbursement Rates: An Assessment of a Natural Experiment

I am grateful to James Poterba, David Cutler, and especially Jonathan Gruber for guidance, and to the National Science Foundation for research support. The MEDPAR data are confidential and cannot be released.

Abstract

Medicare's Prospective Payment System reimburses hospitals a fixed amount for all patients in a given diagnosis-related group (DRG). Little is known about how hospitals respond to changes in these amounts. Increased payments can be used in a number of ways, including more spending on patient care within a DRG subject to a payment increase, more spending on patient care across all DRGs, or no additional spending on patient care at all. This paper investigates this issue by examining the impact of a 1988 modification to the DRG classification system that generated large exogenous increases in fixed payments for certain DRGs. The modification also increased the incentive to "upcode" patients into these more highly-reimbursed DRGs, so after assessing the magnitude of the total reimbursement increase due to the policy change, I investigate the share of the increase that is due to upcoding. I find that the classification change increased reimbursement for the affected DRGs by ~8% relative to unaffected DRGs. Upcoding may have contributed to part of this increase, but the results are inconclusive for hospitals as a group. Among for-profit hospitals, however, upcoding increased markedly following the policy change. Last, I explore where the extra funds were spent, preliminarily ruling out the possibility that the money was used exclusively within the DRGs receiving the payment hikes.

1 Introduction

Hospital objective functions are an empirical enigma. With over 80% of general hospitals under not-for-profit or government management, the industry is a true anomaly within the U.S. economy. Yet to control medical expenditures and to plan for future outlays, it is critical to understand how these institutions respond to changes in financial incentives. The biggest innovation to hospital financing in recent years is the much-studied implementation of the Prospective Payment System (PPS) for Medicare patients, under which hospitals are reimbursed a fixed amount for inpatient visits with the same medical diagnosis. Although these fixed amounts are the centerpiece of the new payment system, very little is known about how hospitals would respond to changes in these amounts. If hospitals are allocated an extra $1000 for heart attack admissions, how much of this money will go to additional treatment for these patients? How much to additional patient care in general? How much to employees, plant and equipment, or shareholders?

These empirical questions are difficult to answer because, for the most part, changes in the fixed payment amounts are driven by changes in costs. Thus, estimates of the effect of reimbursement levels on intensity of care will necessarily be biased unless there is an exogenous change in these reimbursement levels. In 1988, HCFA announced a reform of the diagnosis classification system that generated precisely such a change. This paper estimates the impact of this reform on average reimbursement levels, and begins to investigate hospital responses to the changes in reimbursement.[1]

The classification change was simply the elimination of "age over 69" and "age under 70" in the descriptions for the diagnosis-related groups (DRGs) to which patients may be assigned. Qualifiers that formerly read "with complications or age over 69" and "without complications and age under 69" now read "with complications" or "without complications." This seemingly innocuous change, which is described in greater detail in Section 3, actually led to large increases in reimbursement for the DRG groups formerly assigned to patients with complications or over age 69, and moderate decreases in

[1] All years given in this paper refer to fiscal years (October through September) rather than calendar years.

reimbursement for the DRG groups formerly assigned to young patients without complications.

My analysis addresses three questions: (1) did this shock affect average reimbursement amounts received by hospitals, and if so, by how much? (2) was there upcoding in response to the shock (that is, were patients incorrectly assigned to the "with complications" DRGs), and how much? (3) what was the impact on patient care? I begin by performing an aggregate analysis for each question, using data at the drg/year level. For the first and third questions, there is a natural control group: DRGs that did not have the age/complication qualifier in the pre-shock period. For question 2, I focus on the upcoding incentive created for young patients (age under 70) without complications, so the identification strategy consists of a pre-post comparison of the fraction of young patients coded with complications in the affected DRGs. I then run all of the analyses at the hospital/drg/year level to decompose the results by hospital characteristics.

My analysis shows that the elimination of the age criterion increased reimbursement for affected DRGs by ~8% relative to unaffected DRGs. For-profit hospitals, financially-distressed hospitals, and hospitals in the South were among the big winners from this policy change. The data from the younger patients is consistent with an upcoding response, but because there is a strong pre-shock trend in upcoding (or in the real morbidity of patients), this evidence is inconclusive. Notably, the only hospital characteristic significantly associated with more upcoding is for-profit ownership. While financially-distressed hospitals benefited more from the policy change, this increase does not appear to be due to false reporting (that is, beyond the level exhibited by other hospitals).

Finally, while the policy change increased relative reimbursement dramatically for the affected DRGs, it had no perceptible effect on average charges for patients in those DRGs. Although average charges are only one proxy for intensity of care, this result indicates that the "flypaper effect" may not operate at the DRG level; the additional money does not appear "stick" within the DRGs to which it is assigned.

The remainder of the paper is organized into 5 sections. Section 2 provides background on the PPS system, hospital objective functions, and prior research on average price effects and upcoding. Section 3 gives a detailed explanation of the 1988 policy

change. Sections 4, 5, and 6 present the analyses and discussions of questions 1, 2 and 3, respectively. Section 7 concludes.

2 Background

2.1 A PPS Primer

Understanding the implications of HCFA's policy change requires a brief introduction to PPS. The defining element of the system is a reimbursement amount that is fixed regardless of a hospital's actual expenditures on a patient. This payment varies by the patient's medical diagnosis. Diagnoses are grouped into approximately 500 Diagnosis-Related Groups (DRGs), each of which is assigned a weight (DRG weight) that reflects the relative resource intensity of admissions within that group. Reimbursement to hospital h for an admission in DRG j is given by

$$P_{hj} = \text{DRG weight}_j * P_h * (1 + IME_h) * (1 + DSH_h)$$

where P_h is a hospital-specific amount (inflated annually by a Congressionally-approved "update factor"), IME represents an adjustment for indirect medical education (teaching), and DSH adjusts payment levels to compensate hospitals with a disproportionate share of indigent patients.[2] DRG weights range between .09 and 16.3. HCFA uses hospital charge data to recalibrate the weights annually, raising weights for DRGs that experience a relative increase in average charges, and reducing weights for DRGs with relative decreases in average charges. The average DRG weight per hospital admission, called the *case-mix index*, has risen substantially over time, from 1.20 in 1986 to 1.36 in 1998. This phenomenon is known as "DRG creep," the tendency over time to code more patients in

[2] This formula is from Cutler (1995).

DRGs with higher weights. A 1% increase in the case-mix index is associated with an additional $830 million in *annual* Medicare payments to hospitals.[3]

To the extent that DRGs are truly diagnosis-based, rather than treatment-based, marginal reimbursement for additional services rendered is zero. Average reimbursement, of course, varies according to the formula above. The natural experiment I study changed a number of DRG weights, thus altering average payment levels for all hospitals.

2.2 Hospital Objective Functions

To understand how average reimbursement incentives might affect hospital behavior, it is helpful to introduce a simple model for the hospital objective function. I begin with the traditional assumptions that hospitals attach non-negative weights to both patient care (often called "intensity") and profits, and that the objective function is separable in these arguments:

$$\max\ G = \alpha f(I) + (1-\alpha)\pi$$

where $0 < \alpha < 1$, I denotes intensity, and π denotes profits.

The PPS system effectively defines J "product lines" for the hospital, where J is the number of DRGs. Omitting hospital subscripts for simplicity and postponing upcoding issues for the moment, the hospital selects an intensity level I_j for each DRG j, and attracts $N_j(I_j)$ patients with an average severity level $S_j(I_j)$. Both patient demand and severity are increasing in intensity of care. For each admission, the hospital earns $P_j - C_j(I_j,S_j(I_j))$, where P_j is as defined above, C_j is average cost per patient assigned to DRG j, and $\frac{\partial C_j}{\partial I_j}$ and $\frac{\partial C_j}{\partial S_j}$ are greater than zero.[4] Thus, the hospital's problem becomes

$$\max\ G = \alpha f(I_1,I_2...I_J) + (1-\alpha)\sum_{j=1}^{J}\left([P_j - C_j(I_j,S_j(I_j))]N_j(I_j)\right)$$

[3] The range for DRG weights is given for 1985-1996. The cost associated with a 1% increase in the case-mix index is estimated using 1% of inpatient hospital reimbursements for fiscal year 1998 (*Statistical Abstract of the United States: 1998, No. 172.)*

[4] This cost function is based on the cost function used in Gilman (2000).

and the first-order condition for I_j is

$$\frac{\partial G}{\partial I_j} = \alpha \frac{\partial f}{\partial I_j} + (1-\alpha)\left[(P_j - C_j)\frac{\partial N_j}{\partial I_j} - N_j\left(\frac{\partial C_j}{\partial I_j} + \frac{\partial C_j}{\partial S_j} \bullet \frac{\partial S_j}{\partial I_j}\right)\right] = 0$$

For every DRG, the hospital equates the marginal benefit of intensity to its marginal cost. Differentiating this expression with respect to P_j illustrates that an increase in DRG weight j raises the optimal intensity choice I_j^*:

$$\frac{\partial}{\partial P_j}\left(\frac{\partial G}{\partial I_j}\right) = (1-\alpha)\left[\frac{\partial N_j}{\partial I_j}\right] > 0$$

This result suggests that price increases should be associated with a "flypaper effect" like that observed in many organizations: wherever the money is allocated, that is the area in which it is spent. I test this prediction explicitly in Section 6, by investigating whether hospital charges increased more for DRGs that were more highly reimbursed after the policy change.

There are several reasons such a result may not obtain. First, the link between N_j and I_j may be very weak, reducing the effect of a price increase on intensity levels. Patients may respond to a hospital's overall choice of I, but may be less aware of DRG-specific intensity levels. Second, hospitals may be unable to select different intensity levels for each DRG (i.e. intensity is "lumpy" across DRGs). New technologies or practice patterns, once put in place, may be difficult to apply to only a select group of patients. Third, if intensity choices are not initially in equilibrium, a hospital may allocate new funds earned in affected DRGs to badly-overdue investments in unaffected DRGs.

In addition, hospitals may react differently to the same reimbursement incentives. Any characteristic that alters the parameter α affects the intensity response to a price increase. For example, for-profit hospitals should place a higher weight on profits (lower α), as should hospitals under financial duress. The "mission" of a hospital, reflected in such characteristics as teaching status and certification as a trauma center, may also affect the tradeoff between intensity and profits. Alternatively, different hospitals with the same . may be differentially-equipped to respond to reimbursement incentives. Small hospitals in particular lack the resources needed to reoptimize quickly in the face of price

changes. Finally, there are important regional differences in hospital behavior, although there are no strong theoretical explanations for this phenomenon other than "cultural norms."

The model outlined above can be easily expanded to include upcoding effects. Using U_j as an "upcoding index," the number of patients N_j can be redefined as an increasing function of U_j and a decreasing function of U_{-j}, the degree of upcoding in other DRGs. Holding the number of patients constant, if more patients are upcoded into DRG j, fewer patients are assigned to other DRGs. Similarly, upcoding a patient to DRG j reduces average severity in DRG j (else it would not be upcoding), although the effect on average severity in the original DRG is ambiguous. To summarize,

$$N_j = N_j(I_j, U_j, U_{-j}),\ \frac{\partial N_j}{\partial I_j} > 0, \frac{\partial N_j}{\partial U_j} > 0, \frac{\partial N_j}{\partial U_{-j}} < 0$$

$$S_j = S_j(I_j, U_j, U_{-j}),\ \frac{\partial S_j}{\partial I_j} > 0, \frac{\partial S_j}{\partial U_j} < 0 \quad .$$

Adding a probability of detection . that is increasing in the level of upcoding, a penalty T if the hospital is caught upcoding, and a cost of upcoding R, the objective function becomes

$$G = \alpha f(I_1, I_2 ... I_J) + (1-\alpha)\Big[\sum_{i=1}^{J}\big([P_i - C_i(I_i, S_i(I_i, U_1, U_2 ... U_J))]N_i(I_i, U_1, U_2 ... U_J)\big)$$

$$- \mu(U_1, U_2 ... U_J)T - R(U_1, U_2 ... U_J)\Big]$$

with the following first-order condition for U_j:

$$\frac{\partial G}{\partial U_j} = (1-\alpha)\left[\sum_{i=1}^{J}\left((P_i - C_i)\frac{\partial N_i}{\partial U_j} - N_i\left(\frac{\partial C_i}{\partial S_i} \bullet \frac{\partial S_i}{\partial U_j}\right)\right) - \frac{\partial \mu}{\partial U_j}T - \frac{\partial R}{\partial U_j}\right] = 0 \quad .$$

Hospitals trade off the added revenue (less any change in treatment costs) from shifting patients into higher-weighted DRGs against the increased risk of detection plus the cost of upcoding. In its purest form, upcoding implies no effect whatsoever on the amount of care received by upcoded patients, so treatment costs are unchanged.

Upcoding costs depend on the availability of multiple DRG codes for similar diagnoses. It is theoretically possible to assign a patient with bronchitis to the heart

transplant DRG (weight =13.8 in 1996), but such overt miscoding requires altering medical records substantially and increases the risk of detection later on (whistle-blowers are rewarded by the government). The natural experiment I study affected DRGs that are particularly susceptible to upcoding because these are DRGs for which the same diagnosis has two different codes, one with a significantly higher weight. One former manager from the largest for-profit hospital chain, Columbia/HCA, reported that hospital managers were rewarded for upcoding patients with these diagnoses into the higher-weighted "with complications" codes (Lagnado 1997).

As with intensity levels, there are many reasons that upcoding behavior may differ across hospitals. Hospitals with a lower α will upcode more, while hospitals with a greater penalty T (real or perceived, monetary or otherwise) or a higher probability of detection μ will upcode less. There are a number of theories of the effect of hospital ownership on upcoding, but there are few consensus predictions (see Skinner and Silverman 2000). Hospitals under financial distress should be more willing to risk detection, all things equal, while larger hospitals may be "savvier" in training their coding personnel. The level of local market competition and the practices of competitors may also affect upcoding indirectly through pressure on hospital profits, or directly via the dissemination of upcoding practices. Last, the extent of new upcoding in response to a policy change is limited by the extent of previous upcoding; in the case of the DRGs with and without complications, if an extremely high fraction of patients are already coded with complications, it is not possible to increase this fraction substantially.

This general model of the hospital objective function provides the framework for the empirical analyses I conduct on changes in average reimbursement levels.

2.3 Previous Research

Within the voluminous PPS literature, two distinct lines of research lay the groundwork for the analysis undertaken here. The first consists of a small number of papers that address the impact of average reimbursement amounts on hospital behavior and patient outcomes. The second is the literature on DRG creep, also known as upcoding. These papers attempt

to ascertain how much of the increase in the case-mix index is due to real increases in the morbidity of the patient population, and how much to upcoding by providers.

2.3.1 Average Reimbursement Effects

Virtually all of the papers that evaluate the impacts of PPS do not distinguish between the effects due to changes in marginal reimbursement (during the phase-in of the system) and those due to changes in average reimbursement levels (P_{hj}). The first paper to distinguish these effects is Cutler (1995), which investigates the impact of PPS on adverse medical outcomes. Using discharge data from 1981-1988 in 6 New England states, matched to death records from the Social Security Administration, Cutler finds that the elimination of marginal reimbursement is associated with increased readmission rates, while reductions in average price levels are associated with a compression of mortality rates into the immediate post-discharge period, but no change in mortality at one year post-discharge. The readmission rates appear to be due to "churning" of patients (ostensibly to increase revenue) rather than to changes in patient morbidity.

Of the three additional works that estimate average price responses, two focus on a narrow range of diagnoses (Ellis and McGuire, 1996; Gilman, 2000), while the third investigates cost-shifting responses to changes in the global update factor (Cutler 1998). Ellis and McGuire study New Hampshire's transition to a fixed-price payment system for psychiatric Medicaid patients, concluding that the length of stay for psychiatric inpatients increased in hospitals receiving additional reimbursement for these patients, after controlling for the effect of eliminating marginal reimbursement incentives. Using changes to Medicaid reimbursement for HIV diagnoses in New York, Gilman also finds a positive relationship between reimbursement increases and resource use, where length of stay again proxies for hospital spending. Finally, Cutler (1998) studies the effect of reductions in the update factor on revenue from private patients, documenting a decrease over time in hospitals' ability to offset Medicare reimbursement reductions with price increases to private patients.

The natural experiment I analyze offers two advantages over the payment reforms examined by Cutler (1995), Ellis and McGuire, and Gilman. First, the experiment affects

only average reimbursement levels, so there is no need to make econometric assumptions to disentangle the responses to changes in marginal incentives. Second, the reform was implemented nationwide and affected a large proportion of DRG codes (40 percent). The results should therefore produce the most accurate estimates to date of hospital responses to changes in DRG weights. This paper complements the exploration of across-the-board payment changes in Cutler (1998), although the dependent variables of interest are different.

2.3.2 Upcoding

Because the single largest source of increased hospital spending by Medicare is the rapid rise in the case-mix index, the subject of upcoding has received substantial research attention. Most of this research is dated, focusing on the first few years of PPS. Coulam and Gaumer (1991) review this literature through 1990, concluding that there is evidence of upcoding during the first few years of PPS, but the amount of the case-mix increase attributable to this practice is unknown. More recently, Psaty et al (1999) estimate that upcoding in the heart failure DRG (DRG 127) accounts for nearly $1 billion in annual reimbursements to hospitals, and Silverman and Skinner (2000) document substantial increases in upcoding for pneumonia and respiratory infections between 1989 and 1996.

Silverman and Skinner focus on the share of patients with these diagnoses that are assigned to the most expensive DRG possible, rejecting the argument that the increase in this fraction is due to a real increase in patient morbidity by noting the downward trend in mortality rates for these patients. Interestingly, the authors find that for-profit hospitals upcode the most, and that not-for-profit hospitals are more likely to engage in upcoding when area market share of for-profit hospitals is higher, independently of financial distress and other control variables. This finding is consistent with a contagion model described in Cutler and Horwitz (2000), or an environment dominated by "cultural norms." In addition, hospitals under financial distress upcode *less* than financially sound institutions. My upcoding analysis takes a similar approach, although rather than exploring a time-series trend and relying on mortality rates, which have their own independent trend and are likely to be endogenous to intensity of care, as a control for severity changes, I study an

abrupt change in upcoding incentives that should be met with a similarly abrupt change in upcoding if hospitals are responsive to these incentives. Although I am unable to offer an estimate of the share of DRG creep that is attributable to upcoding more generally, I do calculate a tentative estimate of the share of the shock-related reimbursement increase that is due to upcoding.

3 A Natural Experiment: HCFA's Elimination of the Age $>$ 69/Age $<$ 70 Criterion

From the inception of PPS in 1984 until 1987, 40 percent of the DRG codes included age over 69 or age under 70 as a criterion. Patients with a given diagnosis were classified to a higher-paying code if they were over age 69 *or* had complications (CCs). Thus, there were 95 "pairs" of codes, in which the first code was for diagnosis x for patients over 69 or with CCs, and the second code was for diagnosis x for patients under 70 and without CCs.

In 1987, separate analyses by HCFA and the Prospective Payment Assessment Commission (ProPAC) revealed that "in all but a few cases, grouping patients who are over 69 with the CC patients is inappropriate" (52 *Federal Register* 18877).[5] The ProPAC analysis found that hospital charges for patients over 69 were only 4 percent higher than for patients under 70, while average charges for patients with a CC were 30 percent higher than for patients without a CC. In order to minimize the variation in resource intensity within DRGs and to reimburse hospitals more accurately for the affected diagnoses, HCFA proposed to eliminate the age over 69/under 70 criterion beginning in 1988. They recalibrated the weights for all DRGs to reflect the new classification system. This resulted in a large increase in the first code for the DRG pairs, and moderate declines in the second code.

Table 3 gives the three most commonly-coded pairs and their DRG weights before and after the policy change.[6] These examples are fairly representative of the change

[5] ProPAC, now incorporated into MedPAC (Medicare Payment Advisory Commission), was an independent federal agency that reported to Congress on all PPS matters.

[6] The large volume increase for the second code in each pair is due to the new requirement that uncomplicated patients over 69 be switched from the first to the second code.

overall. Using 1987 admissions from a 20% sample of Medicare discharge data as weights, the weighted average increase in the first code for all affected DRG pairs was 11.2%, while the weighted average decrease in the second code was 6.3%. In the final notice of the policy change, HCFA clearly stated that all weights were recalibrated to ensure no overall change in reimbursement to hospitals; that is, the average national DRG weight (the case-mix index) was constant whether the 1987 or the 1988 classification system (called the GROUPER program) was employed on a given set of discharge records.[7]

However, as the analysis in Section 5 reveals, this policy change resulted in a substantial increase in reimbursement for discharges coded in the DRG pairs. HCFA reported an overall increase of 3.9 percent in the national case-mix index between 1987 and 1988. Although part of this increase was due to real or reported increases in patient severity, in 1989 HCFA concluded that .93% of the increase was due to faulty recalibration of the DRG weights. In addition, mistakes made in recalibrating the 1987 weights caused an unintended increase of .29% in the case-mix index between 1986 and 1987. In response to these findings, HCFA instituted an across-the-board reduction of 1.22% in all DRG weights beginning in 1990. Because this reduction applied uniformly to all DRGs, the large effects on the DRG pairs were unabated.

This policy change provides an excellent opportunity to study hospital responses to changes in DRG levels. After describing my data sources, I analyze the effects of this experiment in three parts. First, I assess the magnitude of the shock to reimbursement levels for affected DRGs. Second, I investigate the role of upcoding in generating the reimbursement increases I identify. Third, I begin to study what hospitals did with the funds.

[7] There were only a few minor changes to the GROUPER program between 1987 and 1988 that were not associated with the elimination of the age criterion.

4 Data

The four main data sources are the 20% Medicare Provider Analysis and Review (MEDPAR) files (1984-1996), the annual tables of DRG weights published in the *Federal Register* (1984-1995), the Medicare Cost Reports (1987), and the *Annual Survey of Hospitals* by the American Hospital Association (1987). The MEDPAR files record data on all hospitalizations of Medicare enrollees, including select patient demographics, diagnoses, charges, and hospital identification number.[8] I use this data to construct volume and charge totals by DRG, hospital, year, and age over 69/age under 70. I then attach the appropriate DRG weights from the *Federal Register*.

To these cells, I match hospital characteristics from the year preceding the shock. From the Cost Reports, which contain annual financial data on all Medicare providers, I extract the least-noisy measure of financial distress available: the hospital's debt:asset ratio. From the *Annual Survey of Hospitals*, I obtain two additional financial distress measures, Medicare "bite" (the fraction of a hospital's discharges reimbursed by Medicare) and Medicaid "bite" (similarly defined), as well as several other hospital characteristics that may be associated with the magnitude of and response to the shock: ownership status (not-for-profit, for-profit, and government), region (South, Northeast, Midwest, West), teaching status, number of general beds and intensive care beds, and service offerings (trauma center, open heart surgery).[9] Last, I add the hospital's case-mix index from 1987, as reported by HCFA. Hospitals with a higher case-mix index should have benefited more from the increase in the ratio of the first to the second codes, as they treat a greater proportion of patients with CCs. Descriptive statistics for the hospital variables are given in Appendix Table 1.

[8] Because FY 1984 begins in October 1983, the study period is 1985-1996.

[9] Virtually all hospitals in the sample had an emergency room, so I omit this seemingly important characteristic from my analysis.

5 Did the Policy Change Matter?

5.1 Effect on Aggregate Reimbursement Levels

For this experiment to provide useful data on hospital responses to reimbursement changes, it is critical to confirm that reimbursement did indeed change. To assess the magnitude of the unintended reimbursement increase that followed the shock, I employ a differences-in-differences technique, comparing the time-series trend in reimbursement for the DRG pairs (henceforth the "affected DRGs") with the trend in reimbursement for the single DRGs (the "unaffected" DRGs). While the DRG weight for the unaffected DRGs is given annually by HCFA, the weight for the affected DRGs is a weighted average of the weights for the first and second codes in each pair. For example,

$$\begin{aligned}\text{weight}_{\text{DRG 138/139, 1988}} = {} & (\text{weight}_{\text{DRG 138, 1988}} * \#\text{ of cases}_{\text{DRG 138, 1988}} + \text{weight}_{\text{DRG 139, 1988}} * \#\text{ of cases}_{\text{DRG 139, 1988}})/ \\ & (\#\text{ of cases}_{\text{DRG 138, 1988}} + \#\text{ of cases}_{\text{DRG 139, 1988}}) \\ = {} & (.8535*35{,}233 + .5912*16{,}829)/(35{,}233+16{,}829) = .7687\end{aligned}$$

I use this formula to calculate the weight for the affected DRGs in every year. To estimate the aggregate impact of the policy change, I assemble a dataset of annual weights for the affected and unaffected DRGs between 1985 and 1996, and estimate the following specifications:

$$(1)\ \ln(\text{weight})_{it} = \alpha + \mu\text{DRG}_i + \lambda\text{year} + [\beta\text{year} * \text{affected DRG}_i\ ] + \varepsilon_{it}$$

$$(2)\ \ln(\text{weight})_{it} = \alpha + \varsigma\text{DRG}_i + \delta\text{year}_t + [\gamma\text{year}_t * \text{affected DRG}_i\ ] + \varepsilon_{it}$$

where i indexes DRGs and t indexes years, affected DRG is a dummy variable that equals one for the treatment group (DRGs affected by the policy change), and the dimensions of the coefficient vectors are μ and ς (1 x 495), λ and β (1 x 1), δ and γ (1 x 11). The interaction terms are bracketed because I estimate these equations both with and without these terms. By using a continuous year variable instead of year dummies, specification (1) permits a tighter estimate of the effect of the policy change, while specification (2) reveals

the exact timing of the impact. Note that the affected DRG fixed effect is absorbed by the inclusion of the DRG fixed effects. Each observation is weighted by the number of discharges for that DRG/year cell.

The results of this analysis are displayed in Table 2. The first two columns present the coefficients from specification (1), first excluding and then including the year*affected DRG interaction term. Similarly, columns three and four contain coefficients from specification (2) with and without the year*affected DRG dummies, respectively. The results indicate a large and statistically significant impact of the policy change on reimbursement for patients assigned to the affected DRGs. While DRG weights declined over time at a rate of .4 percent annually for the unaffected DRGs, they increased by .56 percent annually for the affected DRGs.

The coefficients from specification (2) show that this increase was discontinuous, occurring primarily in 1988, the year of the policy change. Importantly, weights for the affected DRGs did not display a different trend from weights for the unaffected DRGs in the years prior to the shock. These results provide compelling evidence that hospitals were compensated more generously for treating patients in the affected DRG codes following the policy change.

The pattern of coefficients on the year dummies in columns 3 and 4 is also informative, as it summarizes the effects of HCFA's annual recalibrations. In column 3, the declines between 1989 and 1990/91, although not statistically significant, reflect HCFA's across-the-board weight reduction. In column 4, the decline between 1987 and 1988 reflects HCFA's first attempt to maintain overall case-mix neutrality following the policy change.

Summing the year and year*affected DRG coefficients, it is evident that elimination of the age criterion not only caused a *relative* increase in weights for the affected versus the unaffected DRGs, but also an *absolute* increase.

5.1 Effect on Hospital Reimbursement Levels

To answer the question of who benefited the most from this natural experiment, I disaggregate the data into drg/year/hospital cells. I recalculate the weights for the affected DRGs using the formula above, but replacing total volume figures with hospital volume

figures. I then match these cells to hospital characteristics from the 1987 AHA file and the 1987 HCFA Cost Reports, as described in Section 3. To avoid computational problems, I drop data from 1992-1996 in this and all subsequent hospital-level analyses; the impact of the policy change is fully evident by the early 90s, and the 1985-1991 period allows for three years of data before and after the shock.

Finally, I drop all cells pertaining to unaffected DRGs, as all hospitals receive the same DRG weight for admissions to these DRGs. Hospital-level weights vary for the affected DRGs because of differences in the fraction of patients assigned to the first code. I estimate the following regressions:

$$(1)\ \ln(\text{weight})_{iht} = \alpha + \mu DRG_i + \xi X_h + \lambda year + [\varphi X_h \bullet year] + \varepsilon_{iht}$$

$$(2)\ \ln(\text{weight})_{iht} = \alpha + \varsigma DRG_i + \omega X_h + \delta year_t + [\upsilon X_h \bullet year_t] + \varepsilon_{iht}$$

where ξ , φ, and ω are 1 x 19 vectors, and υ is 1 x 114.

Because the main effects are difficult to interpret when all of the interactions are included, the first and third columns of Table 3a contain results from specifications (1) and (2), respectively, before adding these terms. Columns 2 and 4 contain estimates of the main effects from the complete models; the coefficients on the interaction terms are organized in Table 3b. The tables illustrate that while all hospitals gained on average, some gained more than others.

It is helpful to begin with the main effect for each component of X before breaking it out across years. Starting with the ownership variables, for-profit hospitals received 1.3% more on average during the 1985-1991 period than their nonprofit counterparts, while government hospitals were reimbursed .2% more, after controlling for a large number of hospital characteristics as well as the patient case-mix in 1987. Table 3b reveals that these fixed effects are in fact entirely attributable to the post-shock years, when for-profit and government hospitals enjoyed an average reimbursement rate that was 2.2% and .5% higher than not-for-profit hospitals, respectively. Among the many significant interaction terms presented in the table, the FP*year interactions are the most statistically significant, with t-statistics of 32 for FP*year and 13 to 22 for the single year FP interactions after 1987.

These findings foreshadow the main upcoding result presented in the next section: for-profit hospitals engaged in significantly more upcoding following the policy change than did hospitals under not-for-profit or government management.

The positive main effect on the pre-shock case-mix index in columns 1 and 3 indicates that hospitals with sicker patients were reimbursed more on average than hospitals with healthier patient populations. Although hospitals with sicker patients stood to gain more from HCFA's action, the interaction terms in Table 3b show that the effect of case-mix on reimbursement levels fluctuated somewhat during the study period, with a small increase in this effect in 1988 and decreases thereafter. These coefficients suggest that patient severity, as captured by the case-mix index, did not have much to do with who gained from the policy change. One implication of this finding is that upcoding is the more important determinant of the magnitude of the reimbursement increase, although it is possible that the case-mix result reflects a poor correlation across time in hospital case-mix indices.

The pattern of a positive fixed coefficient derived primarily from the post-shock years, as described above for the ownership variables, is repeated for all three of the financial distress variables: debt:asset ratio, share of Medicare discharges, and share of Medicaid discharges. These variables do not affect reimbursement in the pre-shock era, but beginning in 1988, they are strongly associated with increases in reimbursement levels. Hospitals with high Medicaid shares received the most relief from the new policy, with a 2 standard-deviation increase in Medicaid share associated with a ~.82% increase in 1988 reimbursement levels. An increase of 2 standard deviations in the Medicare share and the debt: asset ratio yielded .55% and .62% in extra payments in 1988, respectively.

Finally, the region coefficients also show a pronounced change in the post-shock years, with the omitted region, the South, benefiting more from the policy change than the rest of the country. In addition, small hospitals lost and large hospitals gained relative to medium-sized hospitals (100-200 beds is the omitted category). To the extent that patient complexity increases with hospital size, this pattern is consistent with *a priori* "mechanical" predictions of the policy's effect.

To summarize, the elimination of the age criterion had a large, positive impact on reimbursement for the affected diagnoses. For-profit hospitals, financially-distressed hospitals, and hospitals in the South enjoyed the largest increases in reimbursement.

6 DRG Creep or Jump?

Although upcoding was widely cited as a major source of the increase in the case mix index between 1984 and 1987, HCFA's policy change unwittingly *strengthened* the incentives for hospitals to engage in this practice. The increase in the weight for the first code in an affected DRG relative to the second code provided a strong incentive to keep using the first code for all older patients (not just those with CCs), and to use it more frequently for younger patients. Because all older patients were assigned to the first code in the pre-shock years, upcoding of these patients (i.e. assigning older patients without CCs to the first code after 1988) is impossible to detect without detailed medical records. For this reason, it is also likely that upcoding in this population is more substantial than in the younger group, where upcoding requires shifting more patients into the first code. However, estimates of upcoding from the younger group offer a lower bound on upcoding due to this policy change.

6.1 Aggregate Upcoding Analysis

Using the fraction of patients under 70 who are assigned to the first code in each affected DRG/year group as the dependent variable, I estimate the following specifications:

(1) $\text{fraction}_{it} = \alpha + \mu \text{DRG}_i + \lambda \text{year} + \varepsilon_{it}$

(2) $\text{fraction}_{it} = \alpha + \mu \text{DRG}_i + \delta \text{year}_t + \varepsilon_{it}$

where all notation is unchanged from the reimbursement analysis. Because the dependent variable can only be defined for DRG pairs, all observations are in the treatment group.

Thus, identification of an upcoding response to this policy change requires a discrete jump in the time trend for the fraction variable around 1988.

As the coefficients in Table 4 illustrate, there is such a jump between 1988 and 1989. It is unclear, however, whether this increase represents a significant break from the previous trend. The increase of .045 between 1985 (the omitted year) and 1986 is slightly larger than that between 1988 and 1989 (.039), and the abrupt halt in growth that occurred in 1987 to 1988 (perhaps a response to increased anti-upcoding pressure by HCFA) was too short-lived to firmly establish a new trend. Thus, although the findings from the aggregate analysis are consistent with an upcoding response to the policy change, they are also consistent with an unchanged positive trend in upcoding, or in real severity of patient conditions.

6.2 Hospital Upcoding Analysis

To examine how upcoding changed at the hospital level, I estimate specifications analogous to those described in Section 5.2:

$$(1)\ \text{fraction}_{iht} = \alpha + \mu DRG_i + \xi X_h + \lambda year + [\varphi X_h \bullet year] + \varepsilon_{iht}$$

$$(2)\ \text{fraction}_{iht} = \alpha + \varsigma DRG_i + \omega X_h + \delta year_t + [\upsilon X_h \bullet year_t] + \varepsilon_{iht}$$

Tables 5a and 5b contain the results from these regressions, organized in the same fashion as Tables 3a and 3b. Due to the small number of patients in many DRG/hospital/year cells, the fraction variable fluctuates a great deal and is often 1 or zero. Although I weight each cell by the number of observations it represents, this variation is reflected in the precision of the coefficient estimates, and in the adjusted R-squared, which at .16 is much lower than for the hospital-level regressions presented in Table 3.

There are a number of interesting results from the main effects specifications, of which I will highlight a few, but the most important finding is that the only hospital characteristic clearly associated with upcoding is for-profit ownership status. Although several of the coefficients in φ-hat (listed in the top row of Table 5b) are positive and

statistically significant, indicating an upward trend in the impact of the hospital controls on the fraction of patients coded with complications, the breakdown by year demonstrates that these estimated trends are not, for the most part, due to sudden post-shock changes in the year*interaction coefficients.

On average, for-profit ownership is associated with an additional 3.7% of young patients coded with CCs in 1985-1991, against a universal mean of 67.8%. Most of this increase is due to post-shock upcoding. Interestingly, while the case-mix index is strongly associated with a higher average fraction of patients with complications, the influence of this variable actually diminishes over time. This is the same pattern identified in the hospital-level reimbursement analysis. A possible explanation is that hospitals with high case-mix indices have less room to maneuver upward along this measure.

The main effects of the financial distress variables are all positive and very precisely estimated, indicating that financially-distressed hospitals also report a high proportion of patients with complications. There is no evidence, however, that these hospitals increased their reporting of complicated cases in the post-shock period. The additional payments bestowed on financially-distressed hospitals following the policy change cannot be attributed to upcoding.

Last, the time-series decline in the region effects echoes the finding in Section 5.2: relative to hospitals in the rest of the country, hospitals in the South reported larger increases in the fraction of patients with complications. This trend appears to have begun prior to the shock, however, signaling that the abrupt post-shock reimbursement increase to Southern hospitals was primarily due to the mechanical impact of the policy change.

HCFA's decision to increase the difference between the weights for complicated and uncomplicated patients with the same diagnosis ostensibly widened the aperture to a Pandora's box of upcoding problems. Because DRG creep was so large in the early years of PPS, it is difficult to judge from the time-series data on younger patients how much of the reported increase in complications is due to the heightened incentive presented by the policy change. If *all* of the increase in the fraction of young patients coded with CCs between 1988 and 1989 is due to the policy change (an upper-bound estimate), then upcoding accounted for approximately 3.2% of the 8% increase in reimbursement for

patients in the affected diagnoses.[10] For-profit ownership is associated with 48% more upcoding following the policy change than not-for-profit ownership.[11]

7 Where Did the Money Go?

Whether hospitals received additional reimbursement through HCFA's recalibration error or their own upcoding efforts, there is the all-important question of how the money was spent. Was it spent on patient care, broadly defined to include direct spending during hospital visits (marginal costs) as well as plant and equipment (fixed costs), or on rents to shareholders, salaries to employees, or financial holdings?[12] Was there a flypaper effect, in which hospitals used the increased reimbursement in the affected DRGs to provide more intensive care for patients in those DRGs, or was the money used more globally? To begin answering these questions, I investigate the impact of the policy change on average charges in affected DRGs. Average charges should be positively correlated with the services provided to patients; indeed, this is the measure HCFA uses to calculate DRG weights, so that diagnosis groups with higher average charges are reimbursed more relative to diagnosis groups with lower average charges.

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[10]To obtain this estimate, I multiply the difference in the year coefficients for 1988 and 1989 from the aggregate fraction analysis (Table 4, column 2) by the weighted average ratio for the first to second codes in affected DRGs in 1988 ($ratio_{88}$). This represents the increase in the average DRG weight due to upcoding. I then estimate the 1988 weight as 1 + the weighted average fraction of patients with CCs in 1988*$ratio_{88}$. The ratio of the increase in the DRG weight to the 1988 weight is .032.

[11]The impact of for-profit ownership relative to not-for-profit ownership is estimated using the coefficients from Table 5b in the following formula: $(FP*year_{89} - FP*year_{88})/(year_{89} - year_{88})$.

[12] Duggan (2000) finds that California hospitals that received increased funding through the Disproportionate Share Program (DSH) between 1990 and 1995 (intended to subsidize care for the indigent) used it primarily to increase financial holdings.

7.1 Aggregate Analysis of Charges

To identify the effect of the policy change on aggregate charges, I estimate the same equations used for the aggregate reimbursement analysis, replacing ln(weight) with ln(average charges), deflated to 1985 dollars using the hospital services CPI:

$$(1)\ \ln(\text{average charges})_{it} = \alpha + \mu DRG_i + \lambda year + [\beta year * \text{affected } DRG_i] + \varepsilon_{it}$$

$$(2)\ \ln(\text{average charges})_{it} = \alpha + \varsigma DRG_i + \delta year_t + [\gamma year_t * \text{affected } DRG_i] + \varepsilon_{it}$$

The results of this analysis are displayed in Table 6. Although hospitals were reimbursed more for affected DRGs, they did not spend more on these patients relative to patients in the unaffected DRGs. Overall, charges decreased an average of .62% annually, although the year dummies in columns 3 and 4 illustrate that charges first increased between 1985 and 1989, and decreased thereafter. The point estimates on the year*affected DRG variables are all positive, but none are statistically significant, and the magnitude of the year*affected DRG coefficient decreases rather than increases in the post-shock years. Contrary to the findings of Gilman and Ellis and McGuire that increased reimbursement within DRGs leads to increased treatment intensity for patients in those DRGs, the flypaper effect is not evident, on average, in this experiment.

7.2 Hospital Analysis of Charges

To determine whether individual hospitals responded differently to the reimbursement increase, I estimate the hospital level equations

$$(1)\ \ln(\text{average charges})_{iht} = \alpha + \mu DRG_i + \xi X_h + \lambda year + [\beta year \bullet \text{affected } DRG_i + \theta X_h \bullet \text{affected } DRG_i + \varphi X_h \bullet year + \kappa X_h \bullet year \bullet \text{affected } DRG_i] + \varepsilon_{iht}$$

$$(2)\ \ln(\text{average charges})_{iht} = \alpha + \varsigma DRG_i + \omega X_h + \delta year_t + [\gamma year_t \bullet \text{affected } DRG_i + \chi X_h \bullet \text{affected } DRG_i + \upsilon X_h \bullet year_t + \tau X_h \bullet year_t \bullet \text{affected } DRG_i] + \varepsilon_{iht}$$

where θ, χ, and κ are 1 x 19 vectors, and τ is 1 x 114.

Note that in these regressions, contrary to the previous hospital regressions, it is possible to use the unaffected DRGs as a control. Unlike the weight variable used in Section 5.2, charges for patients in unaffected DRGs can certainly vary across hospitals. The coefficient estimates from these regressions are presented in Tables 7a and 7b. Columns 1 and 3 give results when the bracketed terms are excluded from specifications (1) and (2), respectively, while columns 2 and 4 present the main effects and select second-order interactions from the full models; table 7b gives the third-order interactions. Due to the large volume of coefficients generated by the models in columns 2 and 4, the tables display only the second-order interactions between the year variables and the affected DRG dummy (β-hat and γ-hat), focusing on the third-order interactions that reveal differences in the treatment effect over time and across hospital types.

The main effects in Table 7 offer interesting insights regarding hospital charges within DRGs. Corroborating results from prior research on hospital charges (e.g. Silverman and Skinner 1999), I find that for-profit hospitals charge 24% more than their not-for-profit counterparts, while the smallest hospitals charge 38% less than average-sized facilities. Hospitals with teaching programs, higher debt:asset ratios, larger Medicaid patient shares, and higher case-mix indices also have higher charges, while charges are lower for government hospitals and hospitals with larger Medicare patient shares.

Moving to the year*affected DRG interaction terms, Table 7 confirms the results from Table 6: there was no differential response to the reimbursement shock across treatment groups. In addition, hospitals did not differ in their response (or rather, the lack thereof). Thus, although there were relative winners and losers from the policy change, as well as upcoders and non-upcoders, there was no difference across hospitals in the amount of additional charges for patient care within the affected DRGs.

Although hospital charges are a noisy measure of intensity of care, the results presented in Tables 6 and 7 suggest that hospitals did not allocate relatively more of their

resources to DRGs that were more highly-compensated as a result of the elimination of the age criterion. An important next step is to confirm this result using other measures of intensity of care, such as number of procedures, number of days in intensive care, or length of stay. To understand how the additional funds *were* spent, it will also be necessary to investigate more aggregate measures of hospital expenditure.

8 Conclusion

The analysis presented in this paper shows how a simple change in the DRG classification system generated large changes in average payment incentives. These changes increased Medicare spending by a minimum of half a billion dollars in 1988 and 1989; a 1990 austerity measure eliminated this windfall, but maintained the changes in relative payment levels and therefore left the cross-DRG effect intact.[13]

Much of the change in reimbursement levels is exogenous; that is, it is a mechanical effect due to HCFA's policy change, and not to hospital behavior. However, up to 40 percent of the change in reimbursement levels may be caused by hospital upcoding, clearly an endogenous source. An important next step for this research is to capture the exogenous element of hospital-level weight changes and to see how these changes directly affect hospital behavior. Results from the hospital reimbursement analysis show that the pre-shock case-mix index, theoretically the best instrument for the weight change, is not associated with a post-shock increase in weights for the affected DRGs.

The analysis should also be extended to consider a greater number of hospital responses to the reimbursement changes, as well as the impact of market-level characteristics on these responses. A better understanding of average price effects will help all fixed-price payors to forecast the impact of changes in diagnosis weights, and will inform the broader policy debate on healthcare reform.

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[13] This minimum figure is obtained by multiplying HCFA's own estimate of the increase in the case-mix index due to recalibration mistakes (.93%) by total inpatient spending in 1990 (*Statistical Abstract of the United States: 1998, No. 172.).*

Table 1. **Examples of Policy Change**

DRG code	Description in 1987 (Description in 1988)	1987 weight	1988 weight	% change in weight	1987 volume	1988 volume	% change in volume
96	bronchitis and asthma age>69 and/or CC (bronchitis and asthma age>17 with CC)	0.8446	0.9804	16%	44989	42314	-6%
97	bronchitis and asthma age 18-69 without CC (bronchitis and asthma age>17 without CC)	0.7091	0.7151	1%	4611	10512	128%
138	cardiac arrythmia and conduction disorders age>69 and/or CC (cardiac arrythmia and conduction disorders with CC)	0.8136	0.8535	5%	45080	35233	-22%
139	cardiac arrythmia and conduction disorders age<70 without CC (cardiac arrythmia and conduction disorders without CC)	0.6514	0.5912	-9%	4182	16829	302%
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%	45903	38805	-15%
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%	2033	12363	508%

Notes: Of the 95 affected pairs, these 3 occur most frequently in the 1987 20% MEDPAR sample. Volumes are given for the 20% sample.
Sources: *Federal Register* 51 FR 31454, 52 FR 33034; MEDPAR 20% sample for 1987

Table 2. Aggregate Analysis: Effects of Policy Change on Reimbursement Levels

	Dependent variable is ln(weight) (N = 4382)			
year	-.0016 (.0004)***	-.0040 (.0005)***		
year*affected DRG		.0056 (.0007)***		
year dummies				
1986			-.016 (.006)***	-.022 (.008)***
1987			-.014 (.006)**	-.021 (.008)***
1988			-.014 (.006)**	-.052 (.008)***
1989			-.010 (.006)	-.049 (.008)***
1990			-.020 (.006)***	-.058 (.008)***
1991			-.024 (.006)***	-.058 (.008)***
1992			-.023 (.006)***	-.055 (.008)***
1993			-.023 (.006)***	-.055 (.008)***
1994			-.022 (.006)***	-.054 (.008)***
1995			-.024 (.006)***	-.058 (.008)***
1996			-.023 (.006)***	-.058 (.008)***
*year*affected DRG dummies*				
1986*affected DRG				.013 (.012)
1987*affected DRG				.014 (.012)
1988*affected DRG				.079 (.012)***
1989*affected DRG				.085 (.012)***
1990*affected DRG				.082 (.012)***
1991*affected DRG				.073 (.012)***
1992*affected DRG				.070 (.012)***
1993*affected DRG				.071 (.012)***
1994*affected DRG				.069 (.012)***
1995*affected DRG				.073 (.012)***
1996*affected DRG				.078 (.012)***
DRG fixed effects	Y	Y	Y	Y
Adj. R-squared	0.9763	0.9767	0.9763	0.9771

Notes: The unit of observation for this analysis is DRG/year (where "DRG" refers to single DRGs as well as to DRG pairs). All observations are weighted by the number of procedures recorded in the 20% MEDPAR sample. The sum of the weights is 28.5 million. Year is coded so that 1985=1.

* signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

Table 3a. Hospital Analysis: Effects of Policy Change on Reimbursement Levels

Dependent variable is ln(weight) (N = 1,413,471)												
Main Effects	(1)			(2)			(3)			(4)		
year	0.0054	(.0000)	***	-0.0010	(.0006)							
year dummies												
1986							-0.0091	(.0003)	***	-0.0611	(.0046)	***
1987							-0.0074	(.0003)	***	-0.0683	(.0046)	***
1988							0.0252	(.0003)	***	-0.0627	(.0046)	***
1989							0.0365	(.0003)	***	-0.0266	(.0046)	***
1990							0.0236	(.0003)	***	-0.0297	(.0046)	***
1991							0.0144	(.0003)	***	-0.0410	(.0046)	***
FP	0.0128	(.0003)	***	-0.0080	(.0007)	***	0.0128	(.0003)	***	0.0001	(.0008)	
GOV	0.0022	(.0003)	***	-0.0019	(.0006)	**	0.0022	(.0003)	***	-0.0006	(.0007)	
Case-mix	0.0233	(.0010)	***	0.0165	(.0021)	***	0.0231	(.0010)	***	-0.0109	(.0025)	***
Debt:asset ratio	0.0046	(.0004)	***	-0.0014	(.0008)		0.0046	(.0004)	***	0.0007	(.0009)	
Medicare bite	0.0201	(.0010)	***	-0.0001	(.0023)		0.0203	(.0010)	***	0.0041	(.0026)	
Medicaid bite	0.0220	(.0013)	***	-0.0224	(.0029)	***	0.0219	(.0013)	***	-0.0034	(.0034)	
Northeast	-0.0002	(.0003)		0.0079	(.0006)	***	-0.0001	(.0003)		0.0040	(.0007)	***
Midwest	0.0007	(.0002)	**	0.0087	(.0005)	***	0.0007	(.0002)	**	0.0057	(.0006)	***
West	-0.0007	(.0003)	*	0.0108	(.0006)	***	-0.0009	(.0003)	**	0.0044	(.0008)	***
Teaching	-0.0040	(.0003)	***	-0.0019	(.0008)	*	-0.0039	(.0003)	***	-0.0014	(.0009)	
Open heart surgery	-0.0041	(.0003)	***	-0.0036	(.0007)	***	-0.0040	(.0003)	***	-0.0007	(.0008)	
Trauma facility	-0.0006	(.0002)	**	0.0002	(.0005)		-0.0006	(.0002)	**	0.0002	(.0006)	
<50 beds	-0.0098	(.0005)	***	0.0025	(.0011)	*	-0.0099	(.0005)	***	-0.0019	(.0012)	
50-99 beds	-0.0045	(.0003)	***	0.0012	(.0008)		-0.0045	(.0003)	***	0.0002	(.0009)	
200-299 beds	0.0031	(.0003)	***	-0.0016	(.0007)	*	0.0030	(.0003)	***	-0.0002	(.0008)	
300-400 beds	0.0029	(.0003)	***	-0.0008	(.0007)		0.0029	(.0003)	***	0.0000	(.0009)	
400-500 beds	0.0050	(.0004)	***	-0.0031	(.0009)	***	0.0049	(.0004)	***	-0.0005	(.0011)	
500+ beds	0.0041	(.0005)	***	-0.0030	(.0010)	**	0.0040	(.0005)	***	-0.0001	(.0012)	
#icu beds	0.0000	(.0000)	**	-0.0001	(.0000)	***	0.0000	(.0000)	***	-0.0001	(.0000)	***
Interactions	N			Y (reported below)			N			Y (reported below)		
DRG fixed effects	Y			Y			Y			Y		
Adj. R-squared	0.9395			0.9396			0.9402			0.9404		

Table 3b. Hospital Analysis: Effects of Policy Change on Reimbursement Levels, cont.

Second-Order Interactions (select)			
	FP*	**GOV***	**Case-mix***
year	0.005 (.0002) ***	0.001 (.0001) ***	0.002 (.0005) ***
year dummies			
1986	0.0001 (.0012)	-0.0005 (.0010)	0.0414 (.0036) ***
1987	0.0011 (.0012)	0.0001 (.0010)	0.0483 (.0036) ***
1988	0.0167 (.0012) ***	0.0054 (.0010) ***	0.0560 (.0035) ***
1989	0.0235 (.0012) ***	0.0058 (.0010) ***	0.0360 (.0035) ***
1990	0.0212 (.0012) ***	0.0037 (.0010) ***	0.0325 (.0036) ***
1991	0.0272 (.0012) ***	0.0049 (.0011) ***	0.0259 (.0036) ***
	Debt: asset ratio*	**Medicare bite***	**Medicaid bite***
year	0.002 (.0002) ***	0.005 (.0005) ***	0.011 (.0007) ***
year dummies			
1986	-0.0003 (.0013)	0.0072 (.0037)	-0.0082 (.0048)
1987	0.0002 (.0013)	0.0097 (.0038) **	-0.0057 (.0048)
1988	0.0088 (.0014) ***	0.0251 (.0038) ***	0.0525 (.0048) ***
1989	0.0084 (.0014) ***	0.0232 (.0038) ***	0.0497 (.0048) ***
1990	0.0041 (.0014) ***	0.0197 (.0038) ***	0.0443 (.0049) ***
1991	0.0079 (.0014) ***	0.0321 (.0038) ***	0.0483 (.0049) ***
	Northeast*	**Midwest***	**West***
year	-0.002 (.0001) ***	-0.002 (.0001) ***	-0.003 (.0001) ***
year dummies			
1986	0.0007 (.0010)	-0.0004 (.0009)	0.0029 (.0011) **
1987	-0.0009 (.0010)	-0.0017 (.0009)	0.0011 (.0011)
1988	-0.0020 (.0010)	-0.0045 (.0009) ***	-0.0056 (.0011) ***
1989	-0.0082 (.0010) ***	-0.0082 (.0009) ***	-0.0082 (.0011) ***
1990	-0.0091 (.0010) ***	-0.0098 (.0009) ***	-0.0127 (.0011) ***
1991	-0.0095 (.0010) ***	-0.0103 (.0009) ***	-0.0145 (.0011)
	50-99 beds*	**400-499 beds***	
year	-0.003 (.0001) ***	0.002 (.0002) ***	
year dummies			
1986	-0.0008 (.0017)	0.0014 (.0012)	
1987	-0.0011 (.0018)	0.0009 (.0012)	
1988	-0.0121 (.0018) ***	0.0051 (.0012) ***	
1989	-0.0131 (.0018) ***	0.0035 (.0012) ***	
1990	-0.0172 (.0018) ***	0.0037 (.0012) ***	
1991	-0.0145 (.0018) ***	0.0059 (.0012) ***	

Notes: The unit of observation for this analysis is DRG/hospital/year (where "DRG" refers to DRG pairs). Unaffected DRGs are not included, and hospitals with missing values for any of control variables are dropped. All observations are weighted by the number of admissions recorded in the 20% MEDPAR sample. Year is coded so that * signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

Table 4. Aggregate Analysis: Effects of Policy Change on Upcoding

Dependent variable is fraction of young patients coded with CCs (N=1127)		
year	.0169 (.0004)***	
year dummies		
1986		.0447 (.0056)***
1987		.0813 (.0056)***
1988		.0792 (.0056)***
1989		.1183 (.0056)***
1990		.1355 (.0057)***
1991		.1485 (.0057)***
1992		.1578 (.0057)***
1993		.1714 (.0058)***
1994		.1853 (.0057)***
1995		.1957 (.0057)***
1996		.1941 (.0057)***
DRG fixed effects	Y	Y
Adj. R-squared	0.9164	0.9282

Notes: The unit of observation for this analysis is DRG/year. Unaffected DRGs are not included. All observations are weighted by the number of admissions recorded in the 20% MEDPAR sample. Year is coded so that 1985=1.

* signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

Table 5a. Hospital Analysis: Effects of Policy Change on Upcoding

Dependent variable is fraction of young patients coded with CCs (N = 773,139)				
Main Effects	(1)	(2)	(3)	(4)
year	0.0229 (.0002) ***	0.0291 (.0025) ***		
year dummies				
1986			0.0433 (.0014) ***	-0.0082 (.0183)
1987			0.0770 (.0014) ***	0.0139 (.0184)
1988			0.0667 (.0014) ***	0.0173 (.0183)
1989			0.1119 (.0014) ***	0.1008 (.0183) ***
1990			0.1299 (.0014) ***	0.1382 (.0184) ***
1991			0.1440 (.0014) ***	0.1498 (.0184) ***
FP	0.0369 (.0013) ***	-0.0037 (.0030)	0.0370 (.0013) ***	0.0124 (.0035) ***
GOV	0.0100 (.0012) ***	0.0033 (.0026)	0.0100 (.0012) ***	0.0022 (.0030)
Case-mix	0.1022 (.0038) ***	0.1447 (.0085) ***	0.1025 (.0038) ***	0.0970 (.0099) ***
Debt:asset ratio	0.0119 (.0016) ***	-0.0027 (.0034)	0.0118 (.0016) ***	-0.0130 (.0040) **
Medicare bite	0.0209 (.0042) ***	-0.0198 (.0092) *	0.0207 (.0042) ***	0.0241 (.0108) **
Medicaid bite	0.1330 (.0053) ***	0.1333 (.0117) ***	0.1331 (.0053) ***	0.1354 (.0137) ***
Northeast	-0.0083 (.0011) ***	-0.0036 (.0025)	-0.0082 (.0011) ***	-0.0363 (.0029) ***
Midwest	0.0035 (.0010) ***	0.0264 (.0022) ***	0.0036 (.0010) ***	0.0207 (.0026) ***
West	0.0102 (.0012) ***	0.0420 (.0026) ***	0.0101 (.0012) ***	0.0353 (.0031) ***
Teaching	-0.0085 (.0013) ***	-0.0067 (.0029) *	-0.0085 (.0013) ***	-0.0137 (.0034) ***
Open heart surgery	-0.0152 (.0012) ***	-0.0198 (.0027) ***	-0.0152 (.0012) ***	-0.0094 (.0032) **
Trauma facility	0.0010 (.0009)	0.0023 (.0019)	0.0010 (.0009)	0.0027 (.0023)
<50 beds	-0.0300 (.0023) ***	-0.0260 (.0049) ***	-0.0298 (.0023) ***	-0.0252 (.0056) ***
50-99 beds	-0.0180 (.0015) ***	-0.0126 (.0033) ***	-0.0180 (.0015) ***	-0.0128 (.0039) ***
200-299 beds	0.0091 (.0012) ***	0.0026 (.0027)	0.0090 (.0012) ***	0.0017 (.0031)
300-400 beds	0.0092 (.0013) ***	0.0099 (.0030) ***	0.0092 (.0013) ***	0.0133 (.0035) ***
400-500 beds	0.0171 (.0016) ***	0.0059 (.0036)	0.0170 (.0016) ***	0.0090 (.0043) **
500+ beds	0.0060 (.0018) ***	-0.0184 (.0041) ***	0.0060 (.0018) **	-0.0088 (.0048)
#icu beds	0.0001 (.0000) ***	0.0000 (.0001)	0.0001 (.0000) ***	0.0001 (.0001)
Interactions	N	Y (reported below)	N	Y (reported below)
DRG fixed effects	Y	Y	Y	Y
Adj. R-squared	0.1582	0.1592	0.1592	0.1609

Table 5b. Hospital Analysis: Effects of Policy Change on Upcoding, Continued

Second-Order Interactions (select)			
	FP*	**GOV***	**Case-mix***
year	0.0101 (.0007) ***	0.0017 (.0006) **	-0.0105 (.0019) ***
year dummies			
1986	-0.0030 (.0050)	0.0012 (.0043)	0.0412 (.0141) **
1987	0.0080 (.0050)	0.0096 (.0043) **	0.0451 (.0142) **
1988	0.0279 (.0050) ***	0.0133 (.0043) **	0.0306 (.0141) **
1989	0.0459 (.0050) ***	0.0150 (.0043) ***	-0.0118 (.0141)
1990	0.0360 (.0050) ***	0.0044 (.0043)	-0.0190 (.0141)
1991	0.0562 (.0050) ***	0.0115 (.0044) **	-0.0418 (.0141) **
	Debt: asset ratio*	**Medicare bite***	**Medicaid bite***
year	0.0038 (.0008) ***	0.0105 (.0021) ***	-0.0002 (.0026)
year dummies			
1986	0.0203 (.0057) ***	-0.0409 (.0153) **	0.0002 (.0194)
1987	0.0365 (.0057) ***	-0.0231 (.0155)	0.0018 (.0195)
1988	0.0303 (.0057) ***	-0.0218 (.0154)	0.0018 (.0194)
1989	0.0350 (.0058) ***	0.0090 (.0155)	-0.0197 (.0196)
1990	0.0227 (.0058) ***	0.0080 (.0156)	-0.0146 (.0196)
1991	0.0327 (.0058) ***	0.0539 (.0156) ***	0.0119 (.0198)
	Northeast*	**Midwest***	**West***
year	-0.001 (.0005) *	-0.006 (.0005) ***	-0.008 (.0006) ***
year dummies			
1986	0.0508 (.0041) ***	-0.0038 (.0037)	0.0024 (.0044)
1987	0.0408 (.0041) ***	-0.0145 (.0037) ***	-0.0242 (.0043) ***
1988	0.0443 (.0041) ***	-0.0157 (.0037) ***	-0.0358 (.0043) ***
1989	0.0260 (.0041) ***	-0.0229 (.0037) ***	-0.0374 (.0043) ***
1990	0.0187 (.0041) ***	-0.0293 (.0037) ***	-0.0386 (.0044) ***
1991	0.0154 (.0041) ***	-0.0337 (.0037) ***	-0.0422 (.0044) ***
	50-99 beds*	**400-499 beds***	
year	-0.0009 (.0011)	0.0028 (.0008) ***	
year dummies			
1986	0.0025 (.0082)	0.0030 (.0061)	
1987	-0.0039 (.0083)	0.0050 (.0061)	
1988	-0.0184 (.0083) **	0.0089 (.0060)	
1989	-0.0073 (.0083)	0.0119 (.0060)	
1990	0.0032 (.0083)	0.0054 (.0060)	
1991	-0.0083 (.0084)	0.0228 (.0060)	

Notes: The unit of observation for this analysis is DRG/hospital/year. Unaffected DRGs are not included, and hospitals with missing values for any of control variables are dropped. All observations are weighted by the number of admissions recorded in the 20% MEDPAR sample. Year is coded so that 1985=1.
* signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

Table 6. Aggregate Analysis: Effects of Policy Change on Average Charges

	Dependent variable is ln(average charges) (N = 4382)			
year	-.0068 (.0004)***	-.0073 (.0005)***		
year*affected DRG		.0012 (.0007)		
year dummies				
1986			.0166 (.0057)**	.0103 (.0078)
1987			.0593 (.0057)***	.0497 (.0078)***
1988			.0632 (.0057)***	.0536 (.0078)***
1989			.0688 (.0057)***	.0638 (.0077)***
1990			.0556 (.0056)***	.0516 (.0076)***
1991			.0542 (.0056)***	.0494 (.0076)***
1992			.0553 (.0056)***	.0537 (.0075)***
1993			.0361 (.0056)***	.0320 (.0074)***
1994			.0061 (.0055)	.0016 (.0074)
1995			-.0325 (.0055)***	-.0405 (.0073)***
1996			-.0691 (.0055)***	-.0779(.0073)***
*year*affected DRG dummies*				
1986*affected DRG				.0134 (.0115)
1987*affected DRG				.0210 (.0116)
1988*affected DRG				.0208 (.0115)
1989*affected DRG				.0107 (.0114)
1990*affected DRG				.0084 (.0114)
1991*affected DRG				.0101 (.0113)
1992*affected DRG				.0023 (.0112)
1993*affected DRG				.0083 (.0113)
1994*affected DRG				.0093 (.0111)
1995*affected DRG				.0181 (.0111)
1996*affected DRG				.0203 (.0110)
DRG fixed effects	Y	Y	Y	Y
Adj. R-squared	0.9740	0.9740	0.9793	0.9793

Notes: The unit of observation for this analysis is drg/year (where "drg" refers to single DRGs as well as to DRG pairs). All observations are weighted by the number of admissions recorded in the 20% MEDPAR sample. The sum of the weights is 28.5 million. Year is coded so that 1985=1. Total charges are deflated to $1985 using the hospital services CPI.
* signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

Table 7a. Hospital Analysis: Effects of Policy Change on Average Charges

Dependent variable is ln(average charges) (N = 3,077,971)				
Main Effects	**(1)**	**(2)**	**(3)**	**(4)**
year	0.0080 (.0001) **	0.0124 (.0024)		
year dummies				
1986			0.0206 (.0010) **	0.0687 (.0180) ***
1987			0.0563 (.0010) **	0.0847 (.0180) ***
1988			0.0581 (.0010) **	0.0972 (.0179) ***
1989			0.0563 (.0010) **	0.0804 (.0179) ***
1990			0.0554 (.0010) **	0.0702 (.0177) ***
1991			0.0525 (.0010) **	0.1188 (.0175) ***
FP	0.2361 (.0010) **	0.2149 (.0031) **	0.2362 (.0010) **	0.2218 (.0036) ***
GOV	-0.0710 (.0009) **	-0.0814 (.0027) **	-0.0710 (.0009) **	-0.0810 (.0032) ***
Case-mix	0.1214 (.0028) **	0.0253 (.0081) **	0.1216 (.0028) **	0.0465 (.0097) ***
Debt:asset ratio	0.1621 (.0011) **	0.2106 (.0034) **	0.1620 (.0011) **	0.1906 (.0040) ***
Medicare bite	-0.0416 (.0031) **	0.0271 (.0094) **	-0.0420 (.0031) **	0.0069 (.0111)
Medicaid bite	0.4186 (.0039) **	0.5299 (.0118) **	0.4186 (.0039) **	0.5187 (.0139) ***
Northeast	0.0728 (.0008) **	0.1090 (.0026) **	0.0728 (.0008) **	0.1395 (.0030) ***
Midwest	0.0093 (.0007) **	0.0633 (.0023) **	0.0094 (.0007) **	0.0551 (.0027) ***
West	0.1455 (.0009) **	0.1787 (.0027) **	0.1453 (.0009) **	0.1720 (.0032) ***
Teaching	0.1273 (.0010) **	0.1504 (.0029) **	0.1272 (.0010) **	0.1528 (.0035) ***
Open heart surgery	0.0121 (.0009) **	0.0049 (.0028)	0.0121 (.0009) **	0.0162 (.0034) ***
Trauma facility	-0.0422 (.0007) **	-0.0446 (.0020) **	-0.0422 (.0007) **	-0.0393 (.0024) ***
<50 beds	-0.3776 (.0015) **	-0.4153 (.0048) **	-0.3774 (.0015) **	-0.4206 (.0055) ***
50-99 beds	-0.1813 (.0011) **	-0.2034 (.0034) **	-0.1812 (.0011) **	-0.2080 (.0040) ***
200-299 beds	0.1329 (.0009) **	0.1446 (.0028) **	0.1329 (.0009) **	0.1446 (.0033) ***
300-400 beds	0.1492 (.0010) **	0.1579 (.0031) **	0.1492 (.0010) **	0.1584 (.0037) ***
400-500 beds	0.1772 (.0012) **	0.2084 (.0037) **	0.1771 (.0012) **	0.2064 (.0044) ***
500+ beds	0.1633 (.0014) **	0.2021 (.0042) **	0.1632 (.0014) **	0.1962 (.0050) ***
#icu beds	0.0021 (.0000) **	0.0014 (.0001) **	0.0021 (.0000) **	0.0014 (.0001) ***
Second-Order Interactions (select)				
year*affected DRG		0.0069 (.0036)		
year dummies*affected DRG				
1986*affected DRG				-0.0014 (.0272)
1987*affected DRG				0.0324 (.0272)
1988*affected DRG				0.0300 (.0271)
1989*affected DRG				0.0367 (.0271)
1990*affected DRG				0.0354 (.0271)
1991*affected DRG				0.0446 (.0270)
Second-Order Interactions	N	Y (reported above	N	Y (reported above)
Third-Order Interactions	N	Y (reported below)	N	Y (reported below)
DRG fixed effects	Y	Y	Y	Y
Adj. R-squared	0.5888	0.5897	0.5891	0.5903

Table 7b. Hospital Analysis: Effects of Policy Change on Average Charges, cont.

Third-Order Interactions (select)			
	FP*	**GOV***	**Case-mix***
year*affected DRG	0.0002 (.0010)	0.0005 (.0009)	-0.0031 (.0028)
year dummies			
1986*affected DR	0.0129 (.0074)	-0.0084 (.0065)	0.0046 (.0210)
1987*affected DR	0.0118 (.0075)	0.0004 (.0065)	-0.0262 (.0210)
1988*affected DR	0.0120 (.0074)	-0.0035 (.0065)	-0.0044 (.0208)
1989*affected DR	0.0129 (.0074)	-0.0038 (.0065)	-0.0008 (.0208)
1990*affected DR	-0.0001 (.0074)	0.0016 (.0065)	-0.0101 (.0208)
1991*affected DR	0.0093 (.0074)	-0.0012 (.0065)	-0.0308 (.0207)
	Debt: asset ratio*	**Medicare bite***	**Medicaid bite***
year*affected DRG	0.0013 (.0011)	0.0041 (.0031)	-0.0021 (.0039)
year dummies			
1986*affected DR	-0.0074 (.0082)	0.0170 (.0229)	0.0230 (.0291)
1987*affected DR	0.0061 (.0083)	0.0459 (.0231) *	0.0154 (.0292)
1988*affected DR	0.0014 (.0083)	0.0329 (.0230)	-0.0080 (.0291)
1989*affected DR	-0.0010 (.0084)	0.0243 (.0232)	-0.0163 (.0293)
1990*affected DR	0.0070 (.0084)	0.0151 (.0231)	0.0041 (.0292)
1991*affected DR	0.0032 (.0084)	0.0401 (.0230)	-0.0014 (.0292)
	Northeast*	**Midwest***	**West***
year*affected DRG	0.0006 (.0008)	-0.0012 (.0007)	0.0011 (.0009)
year dummies			
1986*affected DR	-0.0134 (.0063) *	-0.0041 (.0056)	0.0076 (.0066)
1987*affected DR	-0.0075 (.0063)	-0.0025 (.0056)	0.0093 (.0066)
1988*affected DR	-0.0058 (.0063)	-0.0032 (.0055)	0.0100 (.0065)
1989*affected DR	-0.0059 (.0063)	-0.0039 (.0055)	0.0108 (.0065)
1990*affected DR	-0.0024 (.0062)	-0.0034 (.0055)	0.0102 (.0065)
1991*affected DR	0.0004 (.0062)	-0.0103 (.0055)	0.0090 (.0065)
	50-99 beds*	**400-499 beds***	
year*affected DRG	-0.0014 (.0015)	0.0000 (.0012)	
year dummies			
1986*affected DR	0.0086 (.0110)	0.0081 (.0093)	
1987*affected DR	-0.0094 (.0112)	0.0026 (.0093)	
1988*affected DR	-0.0081 (.0113)	0.0021 (.0093)	
1989*affected DR	-0.0038 (.0113)	-0.0013 (.0093)	
1990*affected DR	-0.0146 (.0113)	-0.0010 (.0092)	
1991*affected DR	-0.0005 (.0114)	0.0068 (.0092)	

Notes: The unit of observation for this analysis is drg/hospital/year. The unit of observation for this analysis is drg/hospital/year (where "drg" refers to single DRGs as well as to DRG pairs). All DRGs are included, and hospitals with missing values for any of control variables are dropped. All observations are weighted by the number of admissions recorded in the 20% MEDPAR sample. * signifies p<.05, ** signifies p<.01, *** signifies p<.001

Sources: MEDPAR 20% sample 1984-1996; *Federal Register* 49 FR 34728, 50 FR 35646, 51 FR 31454, 52 FR 33034, 53 FR 38476, 54 FR 36453, 55 FR 35990, 56 FR 39746, 58 FR 46270, 59 FR 45330, 60 FR 45778

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Appendix Table 1. Descriptive Statistics for Hospital Characteristics

Variable	Mean	Std. Deviation	Min	Max
Financial Distress Measures				
Debt:asset ratio	0.535	0.354	0	2.840
Medicare bite	0.374	0.110	0	1
Medicaid bite	0.109	0.082	0	1
Case-mix index	1.138	0.152	0.611	2.188
Region				
Northeast	0.141	0.348	0	1
Midwest	0.301	0.459	0	1
South	0.379	0.485	0	1
West	0.179	0.383	0	1
Service Offerings				
Teaching program	0.056	0.231	0	1
Open heart surgery	0.133	0.340	0	1
Emergency room	0.961	0.194	0	1
Trauma facility	0.185	0.389	0	1
ICU beds (except neonatal)	10.330	12.318	0	194
Size				
1-49 beds	0.215	0.411	0	1
50-99 beds	0.239	0.426	0	1
100-199 beds	0.243	0.429	0	1
200-299 beds	0.132	0.339	0	1
300-399 beds	0.078	0.269	0	1
400-499 beds	0.039	0.193	0	1
500+ beds	0.053	0.225	0	1

Notes: N=5014

Sources: HCFA Cost Reports, American Hospital Association *Annual Survey of Hospitals*, *Federal Register* 51 FR 31454