Managed Care Competition and the Adoption of Hospital Technology: The Case of Cardiac Catheterization †

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Abstract

Diffusion of health care technology is influenced by both the total market share of managed care organizations as well as the level of competition among them. This paper differentiates between HMO penetration and competition and examines their relationship to the adoption of cardiac catheterization laboratories in all non-federal, short-term general community hospitals in the U.S. between 1985-1995. Results show that a hospital is less likely to adopt the technology if HMO market penetration increases but that it is more likely to adopt if HMO competition increases. Further, the competition effect is non-linear. In markets where fewer than 10 neighbors have already adopted, the probability of adoption increases with HMO competition but in markets where 10 or more neighbors have already adopted, the probability of adoption decreases with HMO competition. Thus, in markets where technology is rare, HMO penetration and competition have countervailing effects on the diffusion of technology such that the net effect could be small.

Key words: Managed Care, HMO Competition, Hospital Technology Adoption, Discrete Time Hazard Rate Model

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1. Introduction

The literature on managed care and technology has focused on the relationship of increased health maintenance organization (HMO) penetration and the adoption of expensive technology (Baker and Phibbs, 2002; Baker, 2001; Baker and Brown, 1999; Baker and Spetz, 1999; Chernew, Hirth, Sonnad, Ermann, and Fendrick, 1998; Hill and Wolfe, 1997; Cutler and McClellan, 1996; Baumgardner, 1991) and the medical arms race literature has focused on the role of competition among hospitals and the adoption of technology (Hodgkin, 1996; Chernew, 1995; Dranove, Shanley, and Simon, 1992; Luft, Robinson, Garnick, and Maerki, 1986; Robinson and Luft, 1985; Rapoport, 1978). However, neither has explored the role of increased *competition among HMOs* and the adoption of expensive technology by hospitals. If most markets in the U.S. come to be dominated by a few large HMOs (see Anders and Winslow (1995), Weil (1995)) and to the extent that the flow of new technology is associated with rising health care costs (Newhouse, 1992; Weisbrod, 1991; Baumgardner, 1991; Aaron, 1991), it is important to understand the role of competition among HMOs on the adoption of expensive technologies by hospitals. I do so in this paper.

This paper investigates the interactions among Managed Care Organizations (MCOs), hospitals and the adoption of technology. First, the paper complements prior work by Baumgardner (1991), Baker (2001) and Baker and Phibbs (2002) by extending the discussion to the effect of competition among managed care organizations (MCOs) on hospital technology. Earlier work has typically focused on the impact of increased market share of all MCOs (called penetration) on the diffusion of technology in hospitals. While it is useful to understand the impact of penetration on technology diffusion, it is equally important to take into account the interaction among MCOs and the impact it will have on diffusion of technologies. Chernew, Gowrisankaran, and Fendrick (2002) found that the returns to a hospital from open-heart surgery are lower for HMO patients than for patients with other types of insurance and that in fact the returns vary inversely with the degree of competitiveness within HMOs. The effect on expected profitability of hospitals and hence the diffusion patterns are likely to be very different in two markets where penetration increases from 5% to 30% but in one market there is only one MCO while in the other market more than one MCOs are competing with others for the same market share. Further, I argue that the competition effect is likely to be non-linear in the duplication of technology: When technology is relatively rare, meaning fewer than a critical number of a hospital's neighbors have already adopted the technology in question, increased competition among HMOs leads to a higher probability of adoption, but in markets where technology is already well diffused (more than a critical number of neighbors have already adopted the technology), increased competition will lower the probability of adoption.

Second, support for these claims is provided by empirically analyzing the data on the adoption of cardiac catheterization laboratories from all short-term general hospitals in the U.S. between 1985 and 1995 and the data on HMO penetration and number of HMOs in each market. Using a discrete time hazard rate model, I find that conditional on not having already adopted, in large hospital markets if fewer than about 10 neighbors have already adopted (i.e., the technology is not already well diffused), a hospital is more likely to adopt cardiac catheterization facilities as the competition within HMOs increases. Further, if more than 10 neighboring hospitals have already adopted the technology, then a hospital is less likely to adopt as the competition within HMOs increases. The results are also consistent with previous findings reported in the literature: The probability of adoption, conditional on not already having adopted the technology, decreases with an increase in HMO penetration and increases with the number of neighboring hospitals that have already adopted the technology.

Earlier empirical research that just focused on the relationship of HMO penetration and the adoption of expensive technologies generally found a negative correlation between them. By assuming a proportional hazard for adoption, Cutler and McClellan (1996) estimated the base line hazard semi-parametrically and found that hospitals in areas with high HMO enrollment or with rate regulation are less likely to adopt angioplasty. Cutler and Sheiner (1997) used state level data to examine the relationship between HMO enrollment and the diffusion of 19 technologies, and provided preliminary evidence that managed care reduces the diffusion of medical technologies.[1] Baker and Brown (1999) found that increases in HMO penetration were associated with a reduction in the number of mammography providers. Baker and Spetz (1999) constructed three indices on technology in hospitals using AHA data from 1983 through 1993. A higher value of the index represented the presence of either more services/technologies in a hospital or the presence of relatively rarer technologies. They found that until 1986, the mean value of the technology index was higher for hospitals in markets with high HMO presence, but that beyond 1986 the mean index value was higher for hospitals in markets with low HMO presence. Though their results were not statistically significant for any of the years other than 1993, their results are indicative of a negative correlation between HMO penetration and the presence of technologies. Similarly, Baker (2001) and Baker and

[1] Their measure for diffusion of technology was units per million which they regressed (OLS) on HMO enrollment and other controls.

Phibbs (2002) estimated proportional hazard rate models for the adoption of magnetic resonance imaging (MRI) and neonatal intensive care units respectively and found that hospitals located in markets where HMO penetration was high were less likely to adopt these technologies.

One inference that can be drawn from prior research is that an increase in managed care activity in the U.S. is associated with a slower diffusion of technology. For instance Baker (2001, see p. 415) estimates that there were about 468 fewer MRI adoptions due to managed care. While my own calculations (in the Summary and Conclusions section) also show that an increase in HMO penetration is associated with fewer adoptions of cardiac catheterization laboratories, they also show that an increase in the number of HMOs is associated with more adoptions than there would have been had the number of HMOs stayed small or constant at its 1985 value. In fact, my calculations show that the net impact of increases in HMO penetration and number of HMOs on the adoption of cardiac catheterization has been, at most, very small.

The rest of the paper is organized as follows: The next section summarizes the main arguments of how penetration and competition among managed care organizations may affect hospitals' technology adoption decisions. Section 3 provides a background on cardiac catheterization. Section 4 sets up the adoption model and the testable hypothesis and section 5 describes the data as well as provides estimates of the adoption model. This is followed by a brief Summary and Conclusions section.

2. Hospitals' Adoption Decision and the Role of Managed Care

2.1. **Penetration Effect.** Theoretical as well as empirical literature on technology diffusion has focused on the effect of increased managed care penetration on the adoption of technologies in hospitals. For instance, Baumgardner (1991) classifies new hospital technologies into three classes and considers the adoption of technology under different contract types. Baumgardner links the changes in marginal valuation (to consumers) of the introduction of a technology to the type of insurance contract. On the basis of this assumption he provides testable specifications that suggest that the probability that a hospital will adopt an innovation will depend upon the fraction of customers covered by an HMO versus a traditional fee-for-service (FFS) contract. Similarly Baker and Brown (1999) provide a model that predicts the change in the equilibrium number of (single service) health providers with changes in HMO activity. They predict that the number of providers will increase with an increase in HMO activity for services that are preferred by managed care compared to traditional insurance.[2] More important, their model also predicts that the number of (single service) mammography facilities will always decrease with an increase in managed care activity if the service is relatively less preferred by managed care than by traditional insurance. Both of these models suggest that at least for some technologies, an increase in HMO penetration will discourage technology adoption by hospitals.

By linking changes in the hospitals' expected profitability from adoption of technologies to the timing of adoption (see Rose and Joskow (1990) or Reinganum (1989)) several researchers have recently estimated proportional hazard rate models for adoption of technology in hospitals and found that increases in HMO penetration reduce the adoption hazard. Thus, Cutler and McClellan (1996) estimated the base line hazard semi-parametrically and found that hospitals in areas with high HMO enrollment or with rate regulation are less likely to adopt angioplasty. Similarly, Baker (2001) and Baker and Phibbs (2002) estimate models where the technology of interest is magnetic resonance imaging and neonatal intensive care units respectively and find in both the cases that increases in HMO penetration are associated with a decrease in the adoption hazard.

In all of these empirical papers, the implicit underlying model is one where a hospital adopts a new technology when the discounted expected profit at the given time from adopting the technology is greater than from not adopting it. Baker and Brown (1999), Baker (2001) and Baker and Phibbs (2002) provide an extensive discussion on how managed care could influence the adoption decision by changing the expected profitability of the hospitals. Specifically, they argue that managed care organizations have the ability to change both, the price and volume, of services provided by hospitals which in turn changes the expected profitability of these services and hence the adoption decision in each period (and hence the time to adoption).

In the former case, they argue that because managed care organizations have elastic demand, they bargain aggressively and obtain lower price per service for their enrollees. Thus, if the number of managed care enrollees increases, the expected profitability of the high marginal cost technology decreases for the price discriminating hospitals, which in turn delays adoption of that technology. In the latter case they argue that managed care organizations also affect the adoption decision via influencing the total volume: Because managed care organizations limit the use of expensive (high marginal cost technologies) for their enrollees, they may influence the practicing/prescribing behavior of the in-network physicians such that there is a reduction in the use of services even by the

[2] They stipulate this would happen as long as the loss in profits from increased HMO penetration is smaller than the gain in the profitability from knowledge spill-overs and market expansion.

FFS patients of these physicians. Further, competitive pressures felt by traditional FFS insurance companies may also force them to bring changes in the services they cover. This too implies a reduction in expected profitability which may further delay the adoption of technologies.

2.2. **Competition Effect.** In almost all the papers cited above, an increase in managed care activity is taken to be synonymous with an increase in managed care penetration (i.e., percent of population enrolled in managed care plans). However, changes in penetration levels from 15% to 30% in two otherwise similar markets are likely to affect the expected profitabilities of hospitals (and hence the adoption hazards) very differently if in one market the change is accompanied with just one MCO while in the other market there are several MCOs. Put differently, 20% penetration by one MCO in a market has potentially very different implications for expected profitability of hospitals than a 20% total penetration in the same market split between two or more MCOs. The basic intuition is that neither MCO may have much market power to delay the adoption of expensive technology. Thus, while it is useful to understand the role of penetration, it is equally important to consider the role of increased competition among managed care organizations on the hospitals decision to adopt a technology. It is relatively straight forward to extend Baker's discussion of the impact of managed care on the adoption hazards from impact of increased penetration to increased competition among MCOs.

Price. Consider the price effect. Since MCOs' demand is highly elastic and they bargain with providers for lower price per service for their enrollees, a given MCO can do this effectively if it has a relatively large market share of the MCO market. If on the other hand, the number of MCOs is also relatively large, such that each individual MCO has only a very small share of the market, then getting large price discounts from the hospitals may not be possible. This in turn implies that for a hospital facing a given level of aggregate managed care penetration, expected discounted profits from adoption of a technology at time τ are likely to be higher if the MCO market is less concentrated than when the MCO market is more concentrated. Alternatively, holding penetration constant, the adoption may be delayed if the MCO market is more concentrated.

Volume. Changes in the concentration level of managed care can also change the hospitals expected discounted profits via changes in volume of services provided by hospitals. While each MCO may use (or like to use) mechanisms to induce in-network physicians to lower the use of expensive technologies, their ability to do so may be limited if there are many MCOs competing with each other to sign enrollees and physicians into their network. If competition among MCOs increases, then in order to attract physicians and patients, they would be under greater pressure to relax utilization reviews and other mechanisms by which they control the volume of services provided by hospitals and physicians. Ceteris paribus, the expected profitability for a hospital from the adoption of an expensive technology at time τ will be greater if the competition among managed care organizations is high than if it were low. Additionally, there may be a very limited, or even no change, in the prescribing behavior of the in-network physicians implying a lack of reduction of volume even among the FFS patients seen by the same physicians.

Non-linearities. MCOs compete with each other for enrollees by offering lower premiums and/or access to more service providers with technology. If the technology under consideration has high fixed costs and consumers have a diminishing marginal value in the choice of providers, it is possible that the impact of MCO competition on adoption of technology by hospitals will be non-linear: It will be different depending on whether the technology is already well diffused or if it is still in its early stages of diffusion, i.e., relatively few hospitals have already adopted. (By diminishing marginal value of choice I mean the following: holding price/premium and other things constant, consumers prefer to enroll in MCOs that provide access to more hospitals but this effect diminishes if each MCO contracts with a sufficiently large number of hospitals.[3]) In markets where a large number of service providers have already adopted the technology, MCOs are likely to compete with each other by offering a lower premium to potential enrollees rather than necessarily offering a larger choice set. At the same time, if hospitals set price per service to be at or above the average cost, then those that have not yet adopted the high fixed cost technology can win a contract with MCOs by offering a lower price per service for *other services* (which in turn allows the contracting MCOs to offer a lower premium to the enrollees). Thus, in markets where technology is already well diffused, it is possible that the expected profitability of the hospitals increases (by not adopting) with increased competition among MCOs due to an increase in expected volume of services.

3. CARDIAC CATHETERIZATION

Cardiac catheterization is a procedure during which a thin tube, called a catheter, is threaded into the heart through the arteries to locate and/or to open the blockages using balloons, stents,

[3]As an example, consider the following: If there are two MCOs and two hospitals in a market, and one MCO contracts with only one hospital and the other MCO contracts with both the hospitals, then the MCO with more contracts will steal all (or most of) the enrollees from the competing MCO. However, in a market with ten hospitals and two MCOs, if one MCO has contracts with all ten hospitals and the other has contracts with only nine hospitals, it is no longer true that the MCO with only nine contracts will have no (or very few) enrollees.

roto-rooters etc.[4] If only used diagnostically, the procedure is referred to as an "angiogram" and if also used to open the blockages then it is referred to as an "angioplasty". The procedure takes place in a specialized laboratory in a hospital, called the cardiac catheterization laboratory (henceforth just cathlab). The diffusion of cathlabs provides a good test case to study the impact of managed care on the adoption and diffusion of technologies in the U.S. hospitals. First, it is an expensive technology to adopt as well as an expensive procedure to perform. The presence of HMOs, both their share of market and competition among them, is likely to affect the adoption decisions for this technology. Second, the technology has diffused at a rapid pace during an era when managed care was also growing, making the model estimation procedures feasible. Between 1985 and 1995 the number of hospitals with cathlabs increased from about 18% to 35% while the aggregate U.S. HMO penetration increased from approximately 7% to 20% and the average number of unique HMOs increased from about 4 to 9 per county. Third, the technology is capital intensive and requires many skilled personnel. And fourth, during the study period, it is still mainly a hospital technology, i.e., there are no free standing catheterization laboratories. Thus, as such one does not have to control for the confounding effects on adoption decisions by hospitals due to competition from single service providers.

It was not until 1978 that the first angioplasty was performed in America. The 1980s were marked with incremental product and process innovations in cardiac catheterization. Cardiac stents were first used in 1987, and by the late 1980s and early 1990s, many new devices were introduced, including rotational arthrectomy devices, intravascular ultrasound and lasers (Mueller and Sanborn, 1995; King, 1998, 1996; Meyer, 1990b; Sheldon, 1989; Carlson, 1980). Between 1979 and 1997 the number of cardiac catheterizations increased by about 300% (American Heart Association, 1999). Figure [1] shows the number of cardiac catheterization procedures since 1979 as well as the number of hospitals with cardiac catheterization laboratories.

Like any other technology, the cost of adopting a cardiac catheterization facility varies with time and geographic location. Typically, the cost can be anywhere between $900K to $1.4M (in 1999) for the basic equipment which includes the X-ray machine. Additionally, if a hospital has to undertake building construction for the laboratory room, the construction costs can be up to $7M more. Construction requirements vary by state. For instance, Pennsylvania requires that the

[4] For a balloon angioplasty a catheter with a deflated balloon on its tip is guided over the wire to the blockage and the balloon is then inflated compressing the fatty material against the wall of artery. After the balloon catheter is removed, it leaves a larger opening allowing for improved blood flow to the heart. Using a similar technique, a stent angioplasty leaves a stent inside the artery while a 'roto-rooter' angioplasty shaves the plaque to clean and open the blockage.

laboratory facility have a minimum of 450 square feet area for the laboratory and 150 square feet minimum area for the attached control room, with at least 3 inches of building material between the laboratory and the control room, and a window between the two rooms. Ohio stipulates that the laboratory area must be at least 600 square feet and the attached control room must be at least 90 square feet. In addition to the X-ray machine and the construction costs, various other pieces

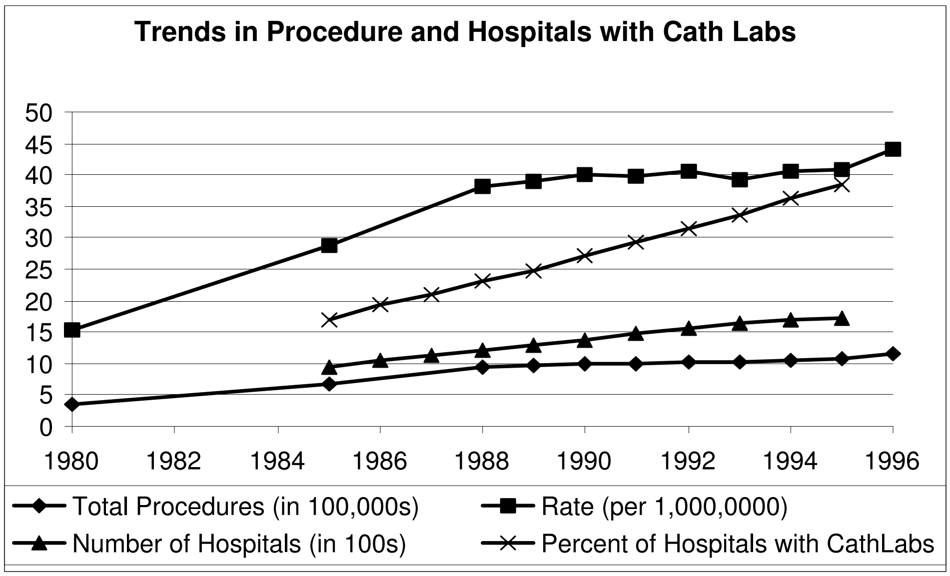

FIGURE 1. Trends in Procedures

of equipment are needed in the laboratory. These include, a physiological monitor ($90K), pressure injector ($35K), external pace maker ($7K), defibrillator ($9K), emergency cart ($2K), protection material for the laboratory personal ($300 a piece), stainless steel tables ($1500), storage cabinets ($3K per unit, need about five of these in a typical laboratory), and finally, film for recording the x-ray images. Initially, 35 mm film were used to capture the results, but the newer facilities have started using cine less film to capture the images digitally on a computer. The electronic archiving costs can be up to $350K per year.

The average cost of an angioplasty (PTCA) in 1995 was $20,370 (American Heart Association, 1999) and the mean charge in 1992 on patients younger than 65 and diagnosed with myocardial infarction was about $10,800 of which 82% of the charges were hospital related, of which about 62% were laboratory charges (Scanlon, Faxon, Audet, et al., 1999). Despite the high costs (of adoption and of procedures) catheterization laboratories have diffused at a rapid pace (see figure [1]). Moreover, the adoption patterns are such that even neighboring hospitals may adopt the technology. The simple reason is that cardiology is a lucrative business. The addition of a catheterization laboratory not only generates catheterization business, but has a 'halo' effect: It attracts patients with other cardiac problems as well more physicians to join the hospital, and through these physicians, attracts yet more patients.[5] (On a related issue, see also Hodgkin (1996)).

4. Adoption Model

4.1. **Hazard Rate Model of Technology Adoption and Managed Care.** Following the large body of empirical literature on technology adoption, I use hazard rate models to estimate the impact of MCOs, both of penetration and competition, on the timing of adoption of cardiac catheterization laboratories (Rose and Joskow, 1990; Cutler and McClellan, 1996; Baker, 2001; Baker and Phibbs, 2002). In a continuous time model, let $\lambda_i(t)$ be the hazard or the instantaneous probability that a hospital adopts a cathlab at time t conditional on it not having adopted it until that point in time and, let $f_i(t)$ and $F_i(t)$ be the corresponding density and cumulative density functions with the usual relationships: $\lambda_i(t) = f_i(t)/S_i(t)$, $S_i(t) = 1 - F_i(t) = \int_t^\infty f_i(\tau)d\tau$ and $S_i(t) = exp\{-\int_0^t \lambda_i(\tau)d\tau\}$. The integral in the curly brackets in the last expression is the cumulative hazard of adoption. Next, allow the hazard to have the proportional form given by $\lambda_i(t) = \lambda_o(t)exp(x_i(t)'\beta)$ where $x_i(t)$ are the time varying hospital specific covariates that effect the hazard rate and $\lambda_o(t)$ is the baseline hazard function that describes the risk for a hospital with $x_i = 0$.

Since the data are observed at discrete time periods, I follow the grouping of continuous time proportional hazard rate models with grouping points at $t_j, j = 1, \ldots, J$ to describe the discrete time proportional hazards model (see Meyer (1990a); Prentice and Gloeckler (1978); Kalbfleisch and Prentice (2002); Cameron and Trivedi (2005)). Let the intervals be $[0, t_1], [t_1, t_2), \ldots, [t_j, \infty)$ then assuming that the hospital specific covariates are constant during each interval (though the hazard itself is not constant during the interval) the expression $exp(x_i(t)'\beta)$ can be pulled out of the integral within a discrete interval. Hence the cumulative adoption probability by the end of

[5] According to one report, (Consumer Reports, 1992) 25% of all hospital revenue is generated from cardiology related procedures and of that 80% comes from just four procedures: cardiac catheterization, angioplasty, bypass surgery and heart-valve surgery. In addition, profit margins for cardiac catheterization are 70% and for angioplasty are 37%, compared to the overall profit margins for hospitals at less than 4%.

period t is given by

$$\begin{aligned} F_i(t) &= 1 - S_i(t) \\ &= 1 - exp\big\{ - \int_0^t \lambda_o(\tau) exp(x_i(t)'\beta) d\tau \big\} \\ &= 1 - exp\big\{ - \sum_{j=1}^{t} exp(x'_{ij}\beta) \int_{t_{j-1}}^{t_j} \lambda_o(\tau) d\tau \big\} \\ &= 1 - exp\big\{ - \sum_{j=1}^{t} exp(x'_{ij}\beta + \lambda_j \big\} \end{aligned} \tag{1}$$

where λ_j is the natural log of the integrated baseline hazard within an interval (i.e., $ln(\int_{t_{j-1}}^{t_j} \lambda_o(\tau) d\tau\})$. If t_j is the first time period during which a hospital is observed to have a cathlab, then $F_i(t_j) - F_i(t_{j-1})$ is the probability that the hospital adopts during the period and $S_i(t_j) = 1 - F_i(t_j)$ is the probability that the hospital has not adopted. Then the the discrete time hazard, or the probability that hospital i adopts a cathlab in period $[t_{j-1}, t_j)$ conditional on not having already adopted by t_{j-1} is given by

$$\lambda_{ij} = Pr[t_{j-1} \leq T_i < t_j | T_i \geq t_{j-1}] = \frac{F_i(t_j) - F_i(t_{j-1})}{1 - F_i(t_j)}. \tag{2}$$

Henceforth refer to the hazard as just the conditional probability (of adoption). Similarly, the likelihood function is given by

$$L = \prod_{i=1}^{N} \Big[F_i(t_j) - F_i(t_{j-1}) \Big]^{c_i} \Big[1 - F_i(t_j) \Big]^{1-c_i} \tag{3}$$

where $c_i = 1$ if the hospital adopts a cathlab and 0 otherwise.

4.2. **Hypothesis.** How does the conditional probability of adoption λ_{ij} change with changes in managed care organization activity? Combining Equations (1) and (2) and simplifying, we get

$$\lambda_{ij} = 1 - exp\{-exp(x'_{ij}\beta + \lambda_j\}. \tag{4}$$

Let x_k be the columns of the matrix of covariates X with x_2 and x_3 being specific measures of MCO penetration and competition in the hospital's market such that higher values mean greater levels of MCO penetration and competition in the market (more on these measures later). While the coefficients on x_2 and x_3 may be negative and positive respectively, the conditional probability itself is not linear in the covariates and could increase or decrease with x_k depending on the value of other covariates (see Equation 2). Specifically, the change in conditional probability of adoption with respect to x_k, i.e., $\partial\lambda_{ij}/\partial x_{ijk}$ could be positive or negative depending upon if the technology is already well diffused in the market or not (henceforth the partial is referred to as the marginal probability) . Thus, if x_5 is a measure of how well the cathlab technology is already diffused in a local market, then based on the discussion in section 2, I state the following hypothesis:

$$\begin{aligned} \frac{\partial \lambda_{ij}}{\partial x_{2ij}} &< 0 \quad \text{for all (reasonable) values of } x_5 \\ \frac{\partial \lambda_{ij}}{\partial x_{3ij}} &> 0 \quad \text{if } x_5 < x_5^* \text{ (technology still diffusing)} \\ \frac{\partial \lambda_{ij}}{\partial x_{3ij}} &< 0 \quad \text{if } x_5 > x_5^* \text{ (technology already diffused)} \end{aligned} \tag{5}$$

where x_5^* is some threshold value of x_5.

5. HMO activity and Cathlab Diffusion

5.1. **Data on HMOs.** There are many types of managed care organizations (PPOs, POS, HMOs etc.) and data on penetration and competition within MCOs should include data from all these organizations. However, good quality and geographically detailed data over the study period is available only for HMOs. Since HMOs were the most prevalent form of managed care activity during this time period and because HMO activity is reasonably correlated with general managed care activity, it may be a decent proxy for managed care. Thus, I use data on HMOs and expect that the coefficients may not be very biased. Further, competition within managed care organizations is crudely measured by the number of HMOs operating in a market rather than the more sophisticated measures such as the Lerner or the Herfindahl-Hirschman Index. This choice of number of HMOs as a measure of HMO competition is due to data limitations which do not allow me to construct these other measures of competition.

The HMO data was provided by Wholey, Feldman, and Christianson (1995) at the Health Services Area (HSA) level as defined by Makuc, Haglund, Ingram, Kleinman, and Feldman (1991); Makuc, Hagland, Ingram, Kleinmann, and Feldman (1991)[6]. This data set is based on InterStudy Censuses (1985 to 1995), InterStudy reports on MSAs served by HMOs, and GHAA Directories (1988 to 1991). The enrollment measure that they construct prorates the enrollment of an HMO over all the counties served by that HMO, using county populations as prorating weights. The information on an HMO's enrollment in an MSA comes from the survey report by InterStudy (1994, 1995). Thus, in their measure, if an HMO operates in two counties with populations of

[6]Briefly, Makuc, Haglund, Ingram, Kleinman, and Feldman (1991); Makuc, Hagland, Ingram, Kleinmann, and Feldman (1991) used 1988 Medicare hospital discharge data to define an HSA as a group of counties such that the flow of hospital patients across HSAs is minimized. They developed an algorithm to cluster counties into a group so that the distance between counties is minimized, where the distance is defined as 1 - total flow of hospital flows between the two counties divided by the total stays in the county with fewer stays.

100,000 and 200,000 then 1/3 of the HMO's enrollment would be reported in the smaller of the two counties and 2/3 would be reported in the larger one. The HMO enrollment measures correct for enrollment reported in the county of the head office location of the individual HMOs. The average number of HMOs per county and the average HMO penetration by year for the data used in this study is summarized in Table 1.

TABLE 1. Number of HMOs and HMO Penetration

Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Avg. # of HMOs	4	5	6	8	8	8	8	8	8	8	9
Avg. Penetration (%)	7.82	9.73	11.54	13.05	13.68	14.35	14.94	15.88	16.28	17.91	20.37

Note: Average penetration is computed as total HMO enrollment in the U.S. in a given year divided by the total U.S. population. Each of these figures was computed by aggregating up the county figures. However, since number of HMOs operating in a county cannot be aggregated up, the figure reported in this table is the weighted average number of HMOs per county where the weights are ratio of county population to U.S. population for that year.

5.2. **Data on Cathlabs.** The data on adoption of cathlabs comes from the American Hospital Association's (AHA) Annual Survey of Hospitals for the years 1985 through 1995. The AHA survey annually collects detailed information on hospital characteristics from nearly all U.S. acute care hospitals and has a response rate of about 90%. This survey includes information on whether or not a hospital offers a particular service/technology. Using hospital ID's, the AHA survey data was linked across years so that each hospital could be followed from 1985 through 1995 inclusive. The base line sample was constructed using all nonfederal short-term general community hospitals with non-missing information on cathlabs and on the covariates for each of the these years. In 1985, there were 5,169 hospitals in the sample of which 775 (15%) had already adopted cathlabs either during that year or in a prior year. Thus, for the base-line analysis, the sample consisted of 4,394 hospitals that were still 'at risk' beginning in 1986. Every year a few new hospitals were added to the analysis sample. This was not because these were necessarily new hospitals per se, but rather because in all the previous years there was missing information on covariates on these hospitals. Thus, for instance, 33 new hospitals were added to the 'at risk' population at the end of 1986. Similarly, if a hospital could not be followed for all the years until 1995, then it was treated as censored. The primary reason for censored observations was that the hospitals merged or exit the market. For instance, 103 hospitals were censored at the end of 1986, most of which exited or merged.

Between 1986 and 1995, the total number of non federal short-term general community hospitals with cathlabs almost doubled – rising from 775 (15%) at the beginning of 1986 to an

Table 2. Summary of Catheterization Laboratory Adoption Data

Adoptions by Short Term General Community Hospitals between 1986 to 1995‡

Year	Hospitals At Risk	Cathlab Adoptions	Censored Exits†	Censored Entries††	Kaplan-Meier Surviver Function $\widehat{S}_t$	Cumulative Adoption Probability $1-\widehat{S}_t$
1986	4394	96	103/8	33/0	0.9782	0.0218
1987	4220	69	120/9	26/5	0.9622	0.0378
1988	4053	83	99/5	30/1	0.9425	0.0575
1989	3897	70	116/7	9/3	0.9255	0.0745
1990	3716	91	100/4	12/12	0.9029	0.0971
1991	3545	92	97/14	11/4	0.8794	0.1206
1992	3357	79	106/4	20/15	0.8587	0.1413
1993	3203	79	289/5	11/6	0.8376	0.1624
1994	2847	60	202/0	7/10	0.8199	0.1801
1995	2602	27	2575/0		0.8114	0.1886

Data Source: American Hospital Association Annual Survey Files

‡ In our sample, 775 hospitals had already adopted cathlabs by 1985. Excluding these, 4,394 hospitals which were at risk were followed from 1986 onwards. However, an additional 159 hospitals joined the 'risk set' starting in a later year making the total sample size of 4,553 unique hospitals that were observed between 1986 and 1995.

† Exits are hospitals that do not adopt in the current year and are (i) either not observed in any of the following years or (ii) reappear in the data set at a later year but not in the following year due to missing covariate values. Thus in 1986, 103 hospitals exit permanently while 8 additional hospitals are missing in 1987 but re-enter the observation set post 1987. Listed exits are counted at the end of the indicated year.

†† Entries are either (i) new hospitals with no observations in any of the prior years or (ii) re-entries by hospitals in the dataset that had a missing covariates in the previous year. Thus in 1994, 7 new hospitals entered the data set while 10 re-entered, i.e., had some missing covariates in 1993 but are in the dataset in earlier years. Listed entries are counted at the end of the indicated year.

additional 746 (about 37%) by the end of 1995 (see Table 2). The percent of hospitals that adopted each year, as a percentage of at risk hospitals fluctuated between 1.04% and 2.60% with an average value of about 2%. The adoption rate was highest in 1991 (2.60% of the at risk population adopted during that year) and progressively slowed down thereafter.

How consistent is the raw data on cathlab adoptions and the number of HMOs (as a rough measure of HMO competition) with the earlier stated hypothesis between these variables? Let the distinction between markets where technology is still diffusing vs. those where it is already well diffused to be simply given by whether a hospital is located in an area where 10 or more of the neighboring hospitals have already adopted cathlab by the previous period. Similarly, for the purpose of counting, let the median number of HMOs (within each of the above categories) be the cutoff for markets with few and many HMOs. After subtracting the 88 adoptions (out of 746) that were in areas that had no HMOs, the count of the number of remaining adoptions by these categories is summarized in Table 3.

TABLE 3. Number of cathlab adoptions broken by – number of HMOs in the area vs. number of neighbors already with cathlabs.

	Technology still diffusing: (Neighbors w. cathlabs < 10)	Technology well diffused: (Neighbors w. cathlabs ≥ 10)
# of HMOs $\leq$ median †	131	126
# HMOs $>$ median †	333	68

† The median value for number of HMOs was 2 for hospitals that were in areas where less than 10 neighbors had already adopted the cathlabs. Similarly, the median value for number of HMOs was 14 for hospitals that had 10 or more neighbors with cathlabs.

There were 464 adoptions by hospitals in areas were technology was still diffusing while 194 were by hospitals in areas where technology was already diffused. When the technology was still diffusing, there were approximately 2.5 times more adoptions when there were many HMOs in the area than when there were few HMOs in the area (333 versus 131). Similarly, of the 194 adoptions by hospitals in areas where technology was already well diffused, there were about 0.6 times fewer adoptions when there were many HMOs in the area than when there were fewer HMOs in the area (68 versus 126). Thus, the counts of number of adoptions as summarized in Table 3 is consistent with the hypothesis about the effect of number of HMOs on adoption probabilities. This cross-tabulation is merely suggestive and I test the hypothesis more formally in the next section.

5.3. **Estimates from Hazard Rate Models.** The adoption model is estimated by maximizing the likelihood function in Equation 3. In addition to measures of HMO activity (penetration and number of HMOs) a number of other hospital specific and area characteristics were also used as model covariates. Information on each hospital's characteristics, such as location, teaching and for-profit status was also obtained from the AHA files. Additionally, for each hospital, I also computed the number of competing hospitals in its local market (both, total number of hospitals as well as hospitals with cathlabs by the previous year), where the local hospital market is defined as the 24-mile radius using the hospitals' ZIP codes. The 24-mile radius hospital market definition has been used before in other studies (Luft, Robinson, Garnick, and Maerki, 1986; Robinson and Luft, 1987; Robinson, Luft, McPhee, and Hunt, 1988) and will be used here as well to facilitate comparison of results with prior research. Finally, variables for demographic and income measures at the county level (population, population over 65, per capita income, AFDC dollars per capita) and variables to capture state level variables (eg. Certificate of Need (CON) laws, the year 10% of farms in the state adopted tractors etc.) were obtained from a number of sources.[7] The data on covariates is summarized in Table 4. As can be seen from Table 4, there is significant amount of variation in

TABLE 4. Descriptive Statistics for variables used in the Hazard Rate Models

Variable	Min	Mean	Std Dev	Max
x_2: HMO penetration	0	8.909	10.9608	70.1748
x_3: #of HMOs	0	5.023	5.899	28
x_4: #of Neighbors	0	10.865	22.314	134
x_5: Neighbors w./ cathlabs last year	0	4.072	9.319	56.5
$x_2.x_5$:(HMO Pen)× (Neighbors w./ cathlabs)	0	79.684	226.248	2516.68
$x_3.x_5$:(#HMOs)× (Neighbors w./ cathlabs)	0	57.894	176.311	1375
x_8: 1/0 Dummy - 1 if CON law in state-year	0	.733	0.442	1
x_9: 1/0 Dummy - 1 if located in a rural county	0	0.0861	0.2805	1
x_{10}: Year 10% of farms adopted tractors	1916.07	1929.69	9.0987	1947.23
x_{11}: per capita income (1982-84 constant 1000's $)	3.645	12.317	3.125	38.12
x_{12}: per capita AFDC $ (1982-84 constant 1000's $)	0	43.462	184.850	1573.25
x_{13}: population over 65 (in 100,000s)	.00183	0.4698	1.2924	9.3063
x_{14}: square of population over 65 (in 100,000s)	3.349E-6	1.8909	10.0963	86.607
x_{15}: total population(in 100,000s)	.01331	4.1103	12.4516	90.642
x_{16}: 1/0 Dummy - 1 if for-profit	0	0.1250	0.3307	1
x_{17}: 1/0 Dummy - 1 if medical school affiliated	0	0.0605	0.2384	1

Note: The statistics are from 1986-1995 pooled observations at the hospital level used to form the 'at risk' study population.

hospital and area characteristics of these hospitals. For instance, HMO penetration ranges from 0 to 70 in the HSA of the hospital while the number of neighboring hospitals ranges from 0 (in rural areas) to about 134 hospitals (very dense areas such as those in Los Angles, New Jersey, New York etc.). While some of the differences in the size of the market (which may influence the adoption decision) can be controlled for via either population variables or dummy variables to indicate that the hospital is located in a rural county, it is possible that the hospitals in rural or very dense areas behave differently than those in the rest of the country. In order to account for such a possibility, I estimated Equation 3 under numerous specifications and under slightly modified versions of the data, i.e., either by dropping observations from rural areas, or from very dense areas, or both. Results are summarized in Table 5 and are labelled '1' through '7' to differentiate between different specifications (detailed version of the results is given in the appendix).

Column 1 provides estimates when all observations (n = 35,834) were used, including hospitals in rural areas as well as those in very dense markets. The coefficient on number of neighbors

[7]These included area Resource File (1996 CD), County Business Patterns (CBP) data, Regional Economic Information System (REIS) (1969-95 CD), Inter-census population estimates and a variety of published reports that contain state level information on Certificate of Need (CON) regulations, "freedom of choice" (FOC) and "any willing provider" (AWP) laws (Marsteller, Bovbjerg, Nichols, and Verrilli, 1997; Conner, Cartwright, and Kole, 1995; Ohsfeldt, Morrisey, Nelson, and Johnson, 1998; National Conference of State Legislatures, 1999; American Health Planning Association, 2000).

TABLE 5. Discrete Time Hazard Rate Estimation

	Specifications (1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Selected Coefficients and Standard Errors[(1)]						
x_2: HMO Penetration	-0.0139^b (.0061)	-.0145^b (.0063)	-.0145^a (.0063)	-.0119^c (.0063)	-.0119^b (.0063)	-.0104^c (.0063)	-.0039 (.0065)
x_3: #of HMOs	.0456^a (.0119)	.0466^a (.0121)	.0465^a (.0121)	.0428^a (.0124)	.0427^a (.0124)	.0406^a (.0124)	.0377^a (.0126)
x_4: #of Neighbors	-.0316^a (.0055)	-.0334^a (.0057)	-.0335^a (.0057)	-.0280^a (.0062)	-.0282^a (.0062)	-.0287^a (.0062)	-.0296^a (.0062)
x_5: Neighbors w./ Cath-labs last year	.1126^a (.0177)	.1200^a (.0183)	.1202^a (.0183)	.1323^a (.0187)	.1324^a (.0187)	.1301^a (.0187)	.1221^a (.0188)
$x_2.x_5$:(HMO Pen)× (Neighbors w./ Cathlabs)	.0006 (.0005)	.0007 (.0005)	.0007 (.0005)	-.0000 (.0005)	-.0000 (.0005)	.0001 (.0005)	-.0002 (.0005)
$x_3.x_5$:(#HMOs)× (Neighbors w./ Cathlabs)	-.0047^a (.0008)	-.0050^a (.0008)	-.0050^a (.0008)	-.0050^a (.0009)	-.0050^a (.0009)	-.0050^a (.0009)	-.0040^a (.0009)
x_8: CON Law Dummy. 1 if law in effect in state-year	– –	– –	– –	– –	– –	.2322^b (.1045)	.1010 (.1075)
x_9: Year 10% of Farms adopted tractors	– –	– –	– –	– –	– –	– –	.0296^a (.0054)
x_{10}: Rural area dummy. 1 if rural area	-3.1563^a (.7095)	-3.1238^a (.7096)	– –	-3.1053^a (.7097)	– –	– –	– –
Marginal with respect to	Selected Marginals ($\frac{\partial \lambda_{ij}}{\partial x_k}$) and Standard Errors						
x_2: HMO Penetration	-.00018^b (.00008)	-.00018^b (.00008)	-.00023^b (.00011)	-.00018^b (.00008)	-.00024^a (.00011)	-.00021^b (.00011)	-.00009 (.00011)
x_3: #of HMOs	.00041^a (.00017)	.00041^a (.00017)	.00050^a (.00022)	.00042^a (.00017)	.00054^a (.00023)	.00049^b (.00023)	.00048^b (.00023)
exclude new hospital obs? [(2)]	x	✓	✓	✓	✓	✓	✓
exclude rural area obs? [(3)]	x	x	✓	x	✓	✓	✓
exclude dense area obs? [(4)]	x	x	x	✓	✓	✓	✓
# of Hospitals @ risk end of '85	4394	4394	4060	4267	3933	3933	3933
# of Observations used	35834	35103	32033	34230	31160	31160	31160
# of Events	746	716	714	708	706	706	706
Log Likelihood	-3374.87	-3246.24	-3228.47	-3195.91	-3178.18	-3175.62	-3160.29

Significance of estimates at 1%, 5% and 10% level indicated by *a b c* respectively. Standard errors are in parenthesis

Note 1 (Other Variables): All specifications include 10 time dummies (i.e., baseline hazard parameters) & variables for per capita income, AFDC per capita, total population, population 65+ and sq. of pop 65+ in the hospital market. Additionally, the regressions also include dummy variables to indicate a hospital's for-profit and teaching school status. Coefficients on these additional variables had expected signs and detailed results are available from the author upon request.
Note 2 (New Hospital Observations): A total of 159 hospitals that entered the observation set post 1986 were dropped from the analysis. See table 2.
Note 3 (Rural Areas Observations): A county is considered rural it is not adjacent to a metro area and if no *area within* the county has population greater than 2,500. For these counties, the total population varies from 1,300 to about 36,000.
Note 4 (Dense Areas Observations): These included hospitals in the following 7 MSAs/PMSAs: Bergen-Passaic, Newark & Jersey City in NJ Los Angeles-Long Beach & Orange Cnty in CA and Nassau-Suffolk & New York City in NY

(x_4) is negative but the coefficient on the number of neighbors with cathlabs (x_5) is positive indicating that it is not the number of neighbors but rather the number of neighbors that offer the same technology in the previous period that increases the likelihood of a hospital to adopt the technology. Similar results were observed by Luft, Robinson, Garnick, and Maerki (1986) when analyzing adoption data on cardiac catheterization. To investigate this aspect further, the model was re-estimated by excluding the variable on the number of neighbors with catheterization laboratories in the previous period from the specification (results not shown). The coefficient on the number of neighbors then became positive and significant. The two results combined indicate that the overall results are consistent with the medical arms race literature.

Consistent with earlier studies (e.g. Baker (2001); Baker and Phibbs (2002)) the coefficient on HMO penetration (x_2) is negative and statistically significant. However, the coefficient on the number of HMOs (x_3) is positive and significant indicating that as HMO competition increases, the adoption hazard increases. To capture the nonlinear effects of these variables on the adoption probabilities, specifically, to estimate the impact of HMO penetration and number of HMOs on adoption probabilities as the level of technology diffusion changes, these two variables were also interacted with the number of neighbors that had already adopted the cathlabs (x_5) by the previous period. While the interaction term with HMO penetration ($x_2.x_5$) is not statistically significant, the interaction term with number of HMOs is negative and statistically significant ($x_3.x_5$). Further, this interaction term is about one order of magnitude smaller than the coefficient on number of HMOs.

In the lower part of Table 5, I provide estimates of the marginal probabilities ($\partial\lambda_{ij}/\partial x_k$ for $x_k = x_2$ and x_3) computed as follows: Let Λ be the transformation such that $\Lambda(I) = 1 - exp(-exp(I))$ where $I = X\beta$ and X is the data matrix which includes dummy variables for each period, then

$$\frac{\partial\lambda_{ij}}{\partial x_k} = \frac{\partial\Lambda}{\partial I}.\frac{\partial I}{\partial x_k} \quad \text{where } \frac{\partial\Lambda}{\partial I} \quad = exp(I - exp(I)). \tag{6}$$

The marginals reported in the table are computed at the sample mean. Thus, in specification 1, at the sample mean, an incremental increase in HMO penetration decreases the probability of adoption (conditional on not having already adopted) by -.00018 while an incremental increase in the number of HMOs increases the adoption probability (conditional on not having already adopted) by +.00041 and the results are statistically significant.[8]

5.4. **Unobserved Heterogeneity. New Hospitals**: Table 2 shows that 159 new hospitals entered the observation set post 1986. These 'new' hospitals were either truly new hospitals or old hospitals

[8] The significance is established by computing the standard errors using the delta method. Thus if $g(\beta) = \frac{\partial\lambda_{ij}}{\partial x_k}$ then $var(g(\beta)) = \bigtriangledown^T g(\beta) V \bigtriangledown g(\beta)$.

with no observations in that AHA files for the previous years, or possibly were the result of mergers. It is possible that these new hospitals could be (partially) deriving the results because they have a different baseline hazard and are in areas where there are more HMOs. To account for this possibility, I omitted all observations on these 159 hospitals and re-estimated the model. The results, given in column 2 of Table 5, are essentially the same as those in column 1 (which include observations on these 159 hospitals). In all remaining specifications, I exclude these 159 hospitals from the analysis.

Hospitals in Rural/Dense Areas: Since it is possible that the hospitals in rural or very dense areas behave differently than those in the rest of the country, I re-estimated the hazard rate model by omitting observations from these areas. Column 3 does not include hospitals that were in rural counties where a county is designated as rural if it is not adjacent to a metro area and no area *within* the county has a population greater than 2,500.[9] Similarly, column 4 drops observations from areas where hospital markets are extremely dense (but does not drop observations from rural areas). The criteria used was to delete observations that had more than 100 neighbors. This resulted in dropping 884 hospital-year observations (132 hospitals) from 7 MSA/PMSAs including those in Bergen-Passaic, Newark & Jersey City in NJ, Los Angeles-Long Beach & Orange County in CA and Nassau-Suffolk & New York City in NY. Similarly, results reported in column 5 drops observations from rural areas as well as those from dense hospital markets. In all three specifications, the results are virtually the same as those in earlier specifications. Particularly, the model coefficients (and standard errors) remain similar to those in earlier specifications. The main difference is that by dropping observations from the rural areas, the point estimates of the marginal probabilities change by a small amount. Upon excluding observations from the rural areas, the marginal probability with respect to HMO penetration changes from -.00018 to about -.00024 and the marginal probability with respect to number of HMOs changes from about .00041 to .00054. Also, dropping observations from the dense areas does not change the results appreciably. Note that these results were robust to alternative definitions of rural counties as well as to alternative cut-offs of 80 and 120 neighbors definition for dense markets. Henceforth, I drop all observations from rural areas and dense areas (and observations on new hospitals).

State Level Differences: States differ in regulating the acquisition of new hospital technologies. Hospitals in states with stricter laws would be less likely to adopt new expensive technologies.

[9] Note that this does not mean that the county population was less than 2,500 – infact the county population for these rural counties varies from about 1300 to about 36,000.

Certificate of Need (CON) laws are one such instrument used by states to control the diffusion of technology (and cost more generally). Since prior research has shown the ineffectiveness of CON laws to reduce the diffusion of technology (or costs) (Salkever and Bice, 1976; Sloan and Steinwald, 1980; Joskow, 1981), it is the primary reason why I have omitted such variables from the present model. (In fact, in a similar hazard rate model, Cutler and McClellan (1996) found the coefficient on the dummy variable for CON laws to be not statistically significant). However, in column 6, I include a simple dummy variable (x_8) to capture if the Certificate of Need (CON) laws were present in the state-year of the hospital.[10] The coefficient on the CON law dummy is positive and significant. This may be due to the fact that states where technologies spread more rapidly were the ones that were more likely adopted these CON laws. However, the coefficients on HMO variables have the same sign and significance as the earlier specifications.

In addition to differences in the regulatory environment across states, there may be a number of other non-tangible variables that may affect the cathlab adoption hazards of hospitals. For instance Skinner and Staiger (2005) show that some states are consistently early adopters of many technologies (hybrid corn, tractors, Beta Blockers etc.) and that these early adopting states also had higher values of social capital. Thus, it may be the case that whatever drives early adoption of various technologies in these states (whether it be social capital or something else) could also influence the adoption probabilities of cathlabs. If any of these variables are correlated with the included variables in the model, for instance if HMOs selectively enter markets with greater social capital, then leaving them out would cause a omitted variable bias.[11] To this end, I re-estimated the model with all variables given in specification 6 but also added a number of variables that capture such non-tangible differences across states (one variable at a time) to assess if the coefficients on HMO related variables change in any significant way. The results from adding one such variable, the year 10% of farms in the state adopted tractors, are given in the column 7. The other variables that I included in the specification (in lieu of the year 10% farms achieved tractors) include, (1) year 10% of farms adopted hybrid corn, (2) percent of farms that adopted tractors in year Y (where Y was 1920, 1930, 1940, 1949, or 1959 respectively), (3) % in homes with computes in 1993, (4)

[10]A simple dummy variable does not capture the intra-state differences in the strictness of these laws (e.g. capital limits) but richer data was not available.

[11]The most straight forward way of dealing with such time-invariant omitted variables is to include state level dummies in the set of control variables. However, such a strategy was not feasible in the current estimation: Including 50 state-level dummy variables on top of the 10 time dummies already included in all specifications (and after dropping observations on new hospitals, rural areas and very dense areas) leaves a total of 706 'events' to be distributed over 50×10 cells. Also note that estimation procedure involves excluding all hospitals from the observation set that had already adopted before 1986 as well as removing all observations on a hospital after it has adopted the technology since the remaining years observations do not make any contribution to the likelihood function. Such a strategy was attempted, but predictably, it lead to non-significance on all the included variables.

Putnum Social Capital Index and, (5) Putnam Education Index. All of these variables are highly correlated with each other and gave the same results as those shown in column 7, specifically, that the coefficient on the HMO penetration variable was not significant but that the coefficient on the number of HMOs stayed positive and significant.

Finally, in all the seven specifications, the marginal probability with respect to number of HMOs at the sample mean is positive, i.e., at the sample mean a small increase in number of HMOs increases the (conditional) probability of adoption (by +.00040 in specification 1 and by +.00048 in specification 7). Similarly, in all specifications the marginal probability with respect to HMO penetration is negative (and in all but the last case is significantly significant – in the last specification, the p-value for the marginal was .21 – the highest ever observed across all specifications including those that are not shown in Table 5).

5.5. **Adoption Probability and Change in Adoption Probability.** In all the seven specifications summarized in Table 5, the coefficient on HMO penetration is negative while that on number of HMOs is positive. However, given the non-linear nature of the hazard (see Equation 4) as well as the interaction terms, it is not immediately clear if the hazard increases or decreases with x_2 and x_3 over the range of the data. For instance, since the coefficient on the interaction term ($x_3.x_5$) between neighbors with catheterization laboratories and number of HMOs is negative and smaller by about an order of magnitude than the coefficient on the number of HMOs (x_3), the slope of the probability curve will become negative when the number of neighbors with a catheterization laboratory is some value slightly greater than ten.

To show this, Figure 2 plots the discrete hazard, i.e., the conditional probability of adoption given that the hospital has not already adopted (see Equation 4) as a function of the number of HMOs where all other variables are at the sample mean but *the number of hospitals that had already adopted in the previous period is fixed at 0,3,6,10,12, and 15 respectively.* The graph shows that as the number of HMOs increase, so does the probability of first and follow-on adoption as long as approximately less than 10 hospitals have adopted the technology. As the number of HMOs in the market increases, the probability of first adoption (neighbors with cathlabs = 0) as well as of duplication (neighbors with cathlabs less than 10) increases, but in markets where the technology is already well diffused an increase in the number of HMOs reduces the probability of further duplication. Thus the slope of these curves (i.e., the marginals with respect to number of HMOs) is positive if the number of hospitals that have already adopted is less than 10, but that the slope becomes negative thereafter.

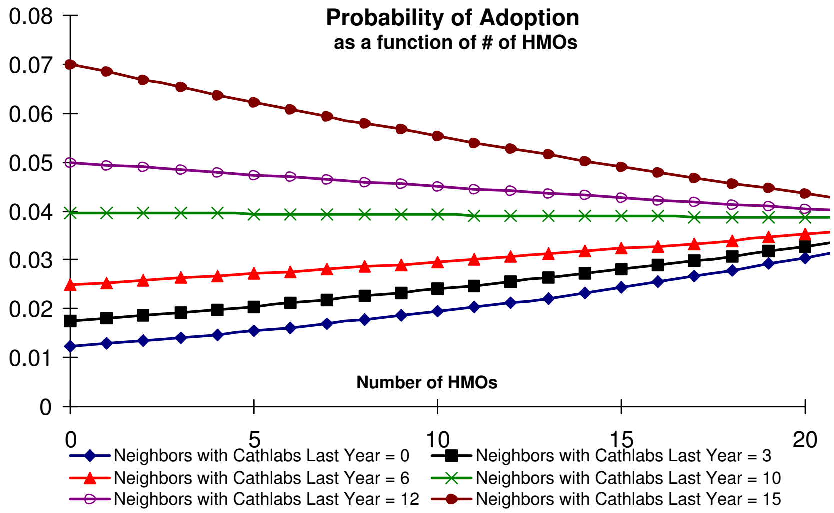

FIGURE 2. Conditional probability of adoption (conditional on not already having adopted) as a function of number of HMOs and neighbors with cathlabs

This difference in the *slope* of the probability curves (i.e., the marginal probabilities) across the neighbors that have already adopted can be made more explicit by computing/simulating the marginal probabilities by the number of neighbors that have already adopted. (Note that these marginal probabilities are already computed at the sample means and are reported in the lower part of Table 5 and varied from .00041 to .00048 across specifications 1 through 7). Thus, Figure 3 plots the marginal probability with respect to number of HMOs (i.e,. $\frac{\partial \lambda_{ij}}{\partial x_3}$) as a function of the number of hospitals that have already adopted the technology in the previous period. The graph is plotted for a market with a large number of hospitals (20-hospital market) and the marginal probability is computed when the number of HMOs is five and HMO penetration is set to about 10%. The error bars show the 95% confidence interval. The figure shows that $\frac{\partial \lambda_{ij}}{\partial x_3}$ is positive until about the 10^{th} adoption and is negative thereafter. However, the positive marginal probability is significant only up to the sixth adoption. Similarly, it becomes negative and significant again after the 15^{th} adoption. Thus, as before, $\frac{\partial \lambda_{ij}}{\partial x_3}$ is positive (and significant) in markets where technology is still diffusing (neighbors with cathlabs < 6) and that $\frac{\partial \lambda_{ij}}{\partial x_3}$ is less than zero in markets where technology is already well diffused.[12]

[12] I also computed the marginal probabilities and 95% confidence intervals for smaller markets, i.e., where the total number of hospitals was five (graphs not shown). In these smaller markets, the marginal probability was positive and significant over the entire range of neighbors with cathlabs: first, second,...fifth adoption. Hence, in both small and large hospital markets, marginal probability of adoption with respect to the number of HMOs is positive.

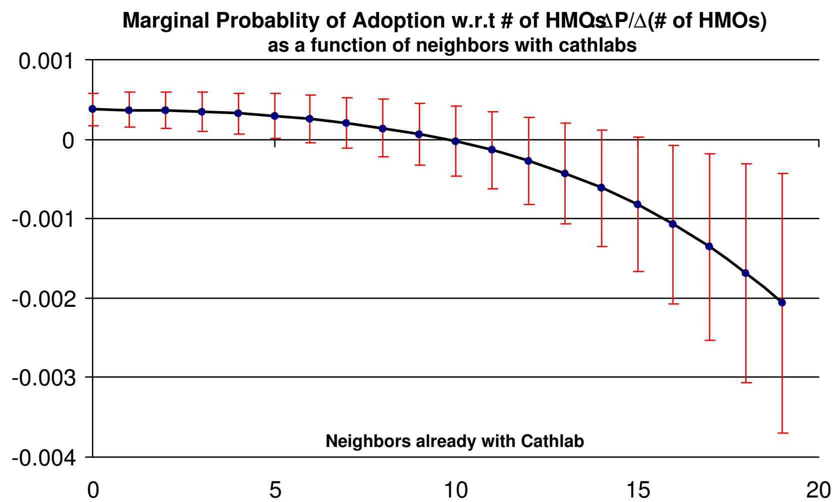

FIGURE 3. Change in (conditional) probability of adoption wrt number of HMOs as a function of number of neighbors with cathlabs

5.6. **Endogeneity.** It is possible that some unobserved local market effects that may be changing over time effect *both,* the hospitals' decision to adopt the technology of interest, and the HMOs' decision to enter the market (and hence HMO penetration level and the level of competition among HMOs). For instance, Baker (1996) and Baker and Spetz (1999) argue that markets with more aggressive practices may be more attractive to HMO entry as well as more likely to adopt technology. If true, failure to include a variable that is correlated with both may lead to the usual omitted variables bias. If the 'aggressiveness' of a market is adequately captured by the variable x_5 (neighbors that have already adopted cathlab by the previous period) then concerns about possible endogeneity due to correlation of the HMO variables with the error term may be alleviated to some extent. However, it is largely an empirical question as to how serious is the potential endogeneity problem.

The standard technique to deal with such endogeneity problems is through the use of instrumental variables (IV), if they are available. Since the duration model used in this study is nonlinear, a standard IV approach is not applicable. However, Cutler and McClellan (1996) suggest using the predicted values of the endogenous variable (hospital competition in their case) as long as the identifying assumption can be made that the average value of the covariates in an area as a whole does not affect a given hospital's decision to acquire the technology once we account for hospital-specific characteristics. It is not clear if such an assumption holds true in the present case. Thus, one alternative is to model an HMO's decision to enter a local market (and its chosen level of output) as well as a hospital's decision to adopt a technology and to write out a likelihood function based on joint distribution of the error terms. The model parameters could then be estimated using the full information maximum likelihood (FIML) estimator. However, one shortcoming of such an estimation strategy is that the estimates of the duration model would not be robust to specification errors in the HMO entry and output (sub-) model.

Alternatively, we can *linearize* the discrete time hazard (i.e., the conditional probability model) and then use the standard IV techniques to assess the seriousness or extent of the potential endogeneity problem. Thus, I first re-estimate the discrete time hazard via a linear probability model and compare it with the results in Table 5. Next, I use the IV methods on the linear probability model to test how much the estimated coefficients change if the HMO variables are truly endogenous but the assumed endogeneity is ignored. While certainly not conclusive, however, if in the linear probability models we find that endogeneity is not a very serious problem (say on the basis of the Hausman test - providing that the instruments are both relevant and valid), then it is *indicative* that the results in Table 5 are not seriously biased on account of endogeneity of the HMO variables.

The conditional probability model is linearized as follows: The discrete time hazard in Equation 4 was generated by grouping time in the continuous-time proportional hazard model into intervals. Alternatively, the conditional probability could also be generated in a model where the hospitals face a binary choice (adopt or not) at discrete points and a hospital adopts if the latent variable (profitability) is greater than some critical value. Then the probability to adopt (conditional on not having already adopted) can be written as $\lambda_{ij} = F(x'_{ij}\beta + \lambda_j)$ where $F(.)$ is the cumulative distribution function of the latent variable. Differences in the distributional assumptions about the error term in the latent variable model allow for different conditional probability models to be estimated. For instance the complementary log-log model in Equation 4 can be derived from the assumption that the latent variable has a standard extreme value distribution. On the other hand, if $F(.)$ is an identity function then we get a linear probability model

$$\lambda_{ij} = Pr[t_{j-1} \leq T_i < t_j | T_i \geq t_{j-1}] = x'_{ij}\beta + \lambda_j + \upsilon_{ij} \tag{7}$$

where x_2, x_3 and their interactions with x_5 are allowed to be correlated with the error term. The linear probability model was estimated using OLS (with robust standard errors due to the introduced heteroscedasticity), H-OLS and H-2SLS and the results are summarized in Table 6.

Instruments. In previous works where linear models were employed, Chernew (1995) suggested using strictness of state regulation and Baker and Spetz (1999) suggested using the number of

TABLE 6. Estimates of the Linear Probability Model For Specification (7)

	Specification (5) Discrete Time Hazard Rate	OLS (Robust)	GMM estimation of Specification (1) as a Linear Probability Model: H-OLS	H-2SLS(A)[†]	H-OLS	H-2SLS(B)[††]
Instruments Used	-	-	z_1, z_2, z_3, z_4		$z_1, z_2, z_3, z_4, z_2 * z_3, z_4 * z_3$	
x_2: HMO Penetration	-.0119^b	-.000342^a	-.000361^a	-.003039^c	-.000356^a	-.001516
	(.0063)	(.000117)	(.000116)	(.001838)	(.000115)	(.001109)
x_3: #of HMOs	.0427^a	.001025^a	.001059^a	.003465	.001055^a	.001716
	(.0124)	(.000314)	(.000309)	(.002342)	(.000309)	(.001612)
x_4: #of Neighbors	-.0282^a	-.000905^a	-.000885^a	-.000836^a	-.000888^a	-.000948^a
	(.0062)	(.000223)	(.000222)	(.000312)	(.000222)	(.000287)
x_5: Neighbors w./ Cath-labs last year	.1324^a	.004584^a	.004583^a	.003467^b	.004595^a	.004555^a
	(.0187)	(.000749)	(.000747)	(.001539)	(.000746)	(.001036)
$x_2.x_5$:(HMO Pen)× (Neighbors w./ Cathlabs)	-.000	.0000018	.0000023	.000224	.0000017	.000049
	(.0005)	(.000147)	(.000032)	(.000182)	(.000015)	(.000067)
$x_3.x_5$:(#HMOs)× (Neighbors w./ Cathlabs)	-.0050^a	-.000176^a	-.000177^a	-.000423^b	-.000176^a	-.000231^a
	(.0009)	(.000032)	(.000032)	(.000202)	(.000032)	(.000082)
	Selected Marginals ($\frac{\partial \lambda_{ij}}{\partial x_k}$) and Standard Errors					
x_2: HMO Penetration	-.00024^a	-.00034^a	-.00035^a	-.00230^b	-.00035^a	-.00135
	(.00011)	(.000110)	(.000109)	(.001346)	(.000109)	(.000986)
x_3: #of HMOs	.00054^a	.00045	.00048^c	.00208	.00048^c	.00096
	(.00023)	(.000295)	(.000290)	(.001844)	(.000290)	(.001481)

Significance of estimates at 1%, 5% and 10% level indicated by *a b c* respectively. Standard errors are in parenthesis.

Note: All specifications include 10 time dummies & variables for per capita income, AFDC per capita, total population, population 65+ and sq. of pop 65+ in the hospital market. Additionally, the regressions also include dummy variables for a hospital's for-profit and teaching school status. These regression exclude observations on new hospitals, hospitals in very dense areas and hospitals in rural areas.

Hausman Endogeneity Tests: $\chi^2_{(df=4)} = 5.108$, Pr = .2764 $\qquad$ $\chi^2_{(df=4)} = 4.089$, P-val = .3941

Valid Instruments Test (Hansen's J-Statistic): $\chi^2_{(df=6-4)} = 1.138$, P-val = .5662

	[†]First-Stage statistics for H-2SLS (A)			[††]First-Stage statistics for H-2SLS (B)		
Endogenous Variables:	R^2	Overall F-test	Weak Insts. F-Test	R^2	Overall F-test	Weak Insts. F-Test
x_2: HMO Penetration	0.4119	864.24	370.26	0.4238	903.70	334.94
x_3: #of HMOs	0.6618	2225.46	1001.15	0.6673	2106.17	721.16
$x_2.x_5$:(HMO Pen)× (Neighbors w./ Cathlabs)	0.8765	2174.43	300.62	0.8888	2364.60	303.68
$x_3.x_5$:(# of HMOs)× (Neighbors w./ Cathlabs)	0.9486	3343.36	667.70	0.9516	3591.42	534.86

large businesses in the county of hospital as the instruments for HMO variables. Since both seem plausible I estimated the equation using both sets of instruments. The strictness of state regulation is measured by the presence of the so-called "any willing provider" (AWP) and "freedom of choice" (FOC) laws, as they apply to HMOs regarding physicians, hospitals and pharmacies. Thus, a total of four instruments were used - (i) z_1 : number of businesses with hundred or more employees in the HSA, (ii) z_2 : a variable indicating the extent of the FOC laws in the state of the hospital, (iii) z_3 : a variable indicating the extent of the AWP laws in the state of the hospital, and (iv) $z_4 = z_1 * x_5$:

a variable constructed from the interaction of z_1 and hospitals that had already adopted cathlabs by the previous period.[13] The IV estimation employed these four basic instruments as well as additional estimations were obtained by using interactions among these four instruments.

OLS estimates of the linear probability (Equation 7) under specification 5 of Table 5 are given in the second column of Table 6 (for comparison, the earlier estimates of specification 5 from Table 5 are repeated in column 1 of Table 6). The signs and significance of the coefficients (using robust standard errors) from OLS estimates of Equation 7 are similar to the maximum likelihood estimates of Equation 4. However, the difference in the magnitude of the coefficients in column 1 and column 2 are somewhat misleading since in the linear model, but for the interaction term, the coefficients are the marginals whereas for the probability model in column 1, the marginals are given by Equation 6. Accounting for the interaction term, the marginals with respect to x_2 and x_3 are reported in the middle section of the table, and these are comparable in magnitude. For instance, the marginal with respect to number of HMOs in specification 5 is .00054 but for the linear model with (robust) OLS estimates it is .00045.

The primary interest here is to see if the coefficients change by a significant amount when the HMO variables and their interaction with x_5 are allowed to be endogenous. To this end, the usual method is to employ the Hausman test, i.e., compute $\chi^2 = (\beta_2 - \beta_1)^T (V_2 - V_1)^{-1} (\beta_2 - \beta_1)$ using coefficients and variance-covariance matrices from OLS and IV estimation and where under the null, OLS is efficient and consistent and IV is consistent. However, because of the introduced heteroscedasticity in the linear probability model, the test is not applicable without some adjustment. Further, a 'robust' adjustment to the variance matrices, both to OLS and IV, will not suffice: It is no longer true that the 'robust' OLS is relatively more efficient than the 'robust' IV when 'robust' OLS is consistent.[14] However, we can construct valid χ^2 statistics using the GMM estimators for heteroscedastic OLS (H-OLS) and heteroscedastic 2SLS (H-2SLS)(Baum, Schaffer, and Stillman, 2003).[15]

[13]Variable z_2 for FOC and z_3 for AWP took four possible values (0,1,2,3) and each variable was constructed by summing three dummy variables indicating if the state had a FOC or AWP law for HMOs regarding (i) physicians, (ii) hospitals, or (iii) pharmacies.

[14]The 'robust' IV is just the Eicker-Huber-White sandwich estimator constructed in the same way as the 'robust' OLS estimator and is given by Robust$\widehat{V}_{iv} = (X'P_zX)^{-1}\Big\{X'Z(Z'Z)^{-1}(Z'\Omega Z)(Z'Z)^{-1}Z'X\Big\}(X'P_zX)^{-1}$.

[15] The H-OLS, due to Cragg (1983), is a two-step GMM estimator that uses the additional moment conditions when there are excluded exogenous instruments and it is asymptotically more efficient than the usual 'robust' OLS estimator under heteroscedasticity. Similarly, the H-2SLS, due to Davidson and Mackinnon (2004, see p.365), is also a GMM estimator and is more efficient than the robust 2SLS estimator.

Using the four instruments given earlier (z_1, z_2, z_3, z_4), the H-OLS and H-2SLS results are summarized in columns 3 and 4 and the marginals are given in the middle section of the table. The coefficients and the marginals both change, though the signs and significance levels stay the same. Further, the differences in the coefficients are not statistically significant. Specifically, the Hausman test constructed as the χ^2 variable with four degrees of freedom has a value of 5.108 with an associated p-value of .2764. Thus, per this test, the null of the adequacy of H-OLS cannot be rejected at the .05 level.[16] Further, note that the computed marginals for the H-OLS results are very similar to the marginals of the hazard rate model of specification 5.

While the Durbin-Wu-Hausman tests do not reject the null of no endogeneity, these tests apply only if the instruments are both relevant (and not weak) and valid (i.e., are orthogonal to the error terms). The 'first-stage' statistics (summarized in the bottom of Table 6) of the four endogenous variables do not indicate that the instruments are weak. In every case, the weak instruments F-test (a restrictions test) is above the rule of thumb value of 10 (see Staiger and Stock (1997)). However, since the linear model is exactly identified (four endogenous variables and four instruments), validity of the instruments via the usual over identification tests can not be ascertained. Thus, I used interactions among the four instruments to get over-identification and then test for orthogonality of these instruments. Further, to see how sensitive these results are to the choice of instruments, I estimated a number of pair of additional H-OLS and H-2SLS models (and computed the χ^2 statistics each time) by varying the set of instruments. The choice of instruments ranged from (1) using all possible interactions among z_1, z_2, z_3, z_4, (2) a parsimonious subset of the interactions (since in the fully interacted model some of the moment conditions are redundant) and, (3) constructing variables z_2 and z_3 in slightly different ways (for instance z_2 and z_3 could each be a set of three different dummy variables capturing information on the FOC and AWP laws).

While all these variations on choice of instruments gave similar results, the results from one such case, where only two interactions (z_2z_3 and z_4z_3) were added to the four initial instruments, are summarized in columns (5) and (6). The Hausman χ^2 statistic for a test of endogeneity has a value of 4.089 with a associated p-value of .3941) implying (again) that the null of 'no endogeneity' cannot be rejected. More importantly, Hansen's J-statistic has χ^2_2 value of 1.138 with two degrees of freedom

[16] This χ^2 statistic was constructed by using H-OLS residuals to compute the H-2SLS var-covariance matrix and is the Durbin version of the test. Two alternative ways of constructing the χ^2 statistic are (1) use own residuals for construction of var-cov matrix for H-OLS and H-2LS (the Hausman version) and (2) use the H-2SLS residuals in construction of the H-OLS var-cov matrix (the Wu version). Under the two alternative methods the χ^2 statistics were 5.825 and 5.911 and lead to the same conclusions.

and has a associated p-value of .5662 implying that the null of orthogonality of the instruments with the error term can not be rejected. Indeed, in all the other choices of the instruments, neither the null of no endogeneity of the HMO variables nor the null of validity of the excluded instruments could ever be rejected.

These results show that potential endogeneity of HMO variables does not pose any serious problem in estimation of the linear probability model when endogeneity is ignored.[17] In turn this *suggests* that, even if HMO variables are endogenous, the coefficients and marginals reported in Table 5 may not be necessarily biased.

6. Summary and Conclusions

Managed care organizations change the incentives faced by health care providers which in turn can have significant implications for the diffusion of technology. Consistent with the empirical results reported in the literature, this paper finds that an increases in HMO penetration is associated with a slower diffusion of technology. However, an increase in competition among the managed care organizations, as measured by the number of HMOs in an area, has a countervailing aggregate effect in that an increase in the number of HMOs is associated with an increase in the probability of adoption of cardiac catheterization laboratories by hospitals. This paper used data on the adoption of cardiac catheterization laboratories from all short term general hospitals in the U.S. between 1985 and 1995 and the data on HMO penetration and number of HMOs in each market to estimate a discrete time hazard rate. Results show that whereas an increase in HMO penetration reduces the conditional probability of adoption, a hospital is more likely to adopt as the competition within HMOs increases. Specifically, the conditional probability to adopt increases with the number of HMOs if the technology is still diffusing, but that it decreases if the technology is already well-diffused. The findings reported here are also consistent with the medical arms race literature in that a given hospital's probability to adopt increases with the number of neighboring hospitals that have already adopted the technology in the previous period. Finally, the main results are robust to alternative specifications. Additionally, linear probability models, with and without the use of instrument variables for possibly endogenous variables for penetration and number of HMOs yield similar results.

[17] While Table 6 reports the results of the linear probability model for specification 5 of Table 5, infact all these tests were also conduced on specification 1,6 and 7 of Table 5 and each time they lead to the same conclusion of no serious impact of endogeneity of the linear probability coefficients.

Given that penetration and competition have opposing effects (if the technology is still diffusing), does an increase in managed care activity slow the diffusion of technology? There is no simple answer, as it depends upon, among other things, the relative change in penetration and number of HMOs in an area. However, we can get a rough sense of how many more or fewer adoptions there might have been if the overall managed care activity had not changed over the study period or if the increase in penetration was accompanied with significant market concentration.

Consider the markets where technology is still diffusing, i.e. ten or fewer neighbors have already adopted the technology. In these markets there were 560 actual adoptions (compared to 746 total adoptions in all markets) and the the average predicted probability of adoption was .017748 and the risk set was 31306 (i.e., hospital-years between 1986 and 1995 composing of hospitals that had not adopted by 1985). Multiplying 31306 by .017748 gives 555.6 as the expected number of adoptions, a number remarkably close to the observed 560 adoptions. This implies that in order to estimate how many adoptions would have taken place had there been only one HMO per market or if the number of HMOs and penetration had stayed at the 1985 levels (or some other such scenario), then assuming a binomial distribution for number of adoptions may not provide a bad approximation.[18]

Thus, in a couple of simple exercises, I recomputed the probability of adoption (i.e., the predicted value) using the estimated regression coefficients and all the data values at their original value except that I changed the data on HMO penetration or the number of HMOs or both. Setting HMO penetration equal to zero changes the predicted number of adoptions to 623 and setting it equal to the average value in 1985 (7.82) changes the predicted adoptions to 577. Both suggest that an increase in HMO penetration resulted in fewer adoptions (by 67 and 22 respectively) than had there been no increase in HMO penetration. However, similar calculations show that had there been exactly one HMO in each market and everything else remained the same (including HMO penetration) then the number of adoptions would have been only 492 (or if penetration is kept at the 1985 level then there would have been 506 adoptions). Thus, the presence of additional HMOs can be associated with 64 additional adoptions.

Finally, the net impact of HMOs (due to number of HMOs and HMO penetration) can be judged by setting either both variables to zero or to their 1985 values. Doing so results in 531 and 548 adoptions respectively, both of which are not very far from the true predicted value of 556,

[18] This assumption is technically not correct. A random variable Y where Y is the number of successes observed during n trial requires that each trial be independent. That is not so in the current model. If a hospital adopts the technology, its neighbors are also more likely to adopt in the next period.

suggesting that the *net impact of HMO activity on the adoption of cathlabs has been very small*.[19] If the results reported here for cardiac catheterization are typical for other expensive technologies with high sunk/high fixed costs as well, then the implication is that increased competition among HMOs limits their ability to slow down the diffusion of technology.

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[19]These estimates are very rough since no corrections are made to account for the fact that the adoptions are not truly independent: If one less hospital adopts in a market due to fewer HMOs, then in the next period, the neighboring hospitals would have one less neighbor with the technology and hence the total probability of adoption for each of the neighbors would further decrease. The second order corrections to the estimate can be made as follows: Separate the data by years and for each year generate Bernoulli outcomes (1 for adoption and 0 for non-adoption) with the probability of success p given by the scenario. Next, for each year, count the number of neighbors that have adopted (i.e., the Bernoulli successes plus the number of adopters in 1985). Use this figure to recompute the number of neighbors with catheterization laboratories in the previous year and then simulate to estimate the new probability of adoption. This approach was not taken due to the high cost of computing time. In order to compute how many of the neighbors have adopted the technology, a $n \times n$ contingency matrix must be created for every year where the i,j entry of the matrix (a 1 or a 0) indicates if j is a neighbor to i and n is the number of hospitals in the U.S. in that year. This matrix must then by multiplied with a $n \times 1$ vector which indicates that the ith. hospital has a catheterization laboratory. The matrix multiplication provides the number of neighbors that a hospital has with catheterization laboratory. This method was used in the main analysis to compute the number of neighbors and neighbors with catheterization laboratories and took the bulk of the computing time.

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Appendix

This table provides a detailed version of Table 5 from the paper and includes MLE estimates for variables that were not reported there. It is intended for use by referees and the co-editor and not part of actual paper.

Variable	Detailed version of Table 5 (1)	(2)	(3)	(4)	(5)	(6)	(7)
x_1: Intercept	-5.7806^a (.2596)	-5.8980^a (.2707)	-5.9462^a (.2743)	-5.9529^a (.2774)	-6.0028^a (.2812)	-6.1562^a (.2908)	-63.4287^a (10.4283)
x_2: HMO Penetration	-0.0139^b (.0061)	-.0145^b (.0063)	-.0145^a (.0063)	-.0119^c (.0063)	-.0119^b (.0063)	-.0104^c (.0063)	-.0039 (.0065)
x_3: #of HMOs	.0456^a (.0119)	.0466^a (.0121)	.0465^a (.0121)	.0428^a (.0124)	.0427^a (.0124)	.0406^a (.0124)	.0377^a (.0126)
x_4: #of Neighbors	-.0316^a (.0055)	-.0334^a (.0057)	-.0335^a (.0057)	-.0280^a (.0062)	-.0282^a (.0062)	-.0287^a (.0062)	-.0296^a (.0062)
x_5: Neighbors w./ Cathlabs last year	.1126^a (.0177)	.1200^a (.0183)	.1202^a (.0183)	.1323^a (.0187)	.1324^a (.0187)	.1301^a (.0187)	.1221^a (.0188)
$x_2.x_5$:(HMO Pen)× (Neighbors w./ Cathlabs)	.0006 (.0005)	.0007 (.0005)	.0007 (.0005)	-.0000 (.0005)	-.0000 (.0005)	.0001 (.0005)	-.0002 (.0005)
$x_3.x_5$:(#HMOs)× (Neighbors w./ Cathlabs)	-.0047^a (.0008)	-.0050^a (.0008)	-.0050^a (.0008)	-.0050^a (.0009)	-.0050^a (.0009)	-.0050^a (.0009)	-.0040^a (.0009)
x_8: CON Law Dummy. 1 if law in effect in state-year	- -	- -	- -	- -	- -	.2322^b (.1045)	.1010 (.1075)
x_9: Year 10% of Farms adopted tractors	- -	- -	- -	- -	- -	- -	.0296^a (.0054)
x_{10}: Rural area dummy. 1 if rural area	-3.1563^a (.7095)	-3.1238^a (.7096)	- -	-3.1053^a (.7097)	- -	- -	- -
x_{11}: per capita income (1982-84 constant 1000's \$)	.0661^a (.0146)	.0686^a (.0150)	.0691^a (.0150)	.0717^a (.0157)	.0723^a (.0157)	.0690^a (.0159)	.0864^a (.0159)
x_{12}: per capita AFDC \$ (1982-84 constant 1000's \$)	-.0029^a (.0009)	-.0029^a (.0009)	-.0029^a (.0009)	-.0023^b (.0010)	-.0023^b (.0010)	-.0024^b (.0010)	-.0015 (.0010)
x_{13}: population over 65 (in 100,000s)	.4441^a (.1301)	.4515^a (.1338)	.4510^a (.1338)	.4246^a (.1353)	.4241^a (.1353)	.3537^b (.1396)	.3410^b (.1379)
x_{14}: square of population over 65 (in 100,000s)	.0131 (.0186)	.0124 (.0189)	.0127 (.0189)	.0113 (.0204)	.0116 (.0204)	.0074 (.0205)	-.0035 (.0207)
x_{15}: total population (in 100,000s)	-.0042 (.0155)	-.0049 (.0158)	-.0051 (.0158)	-.0122 (.0159)	-.0123 (.0159)	.0021 (.0172)	.0020 (.0171)
x_{16}: 1/0 Dummy - 1 for-profit	-.0092 (.1130)	.0202 (.1151)	.0209 (.1151)	.0318 (.1157)	.0326 (.1157)	.0500 (.1161)	-.1038 (.1185)
x_{17}: 1/0 Dummy - 1 if medical school affiliated	.9668^a (.1044)	.9697^a (.1068)	.9698^a (.1069)	.9483^a (.1078)	.9484^a (.1078)	.9303^a (.1080)	.8940^a (.1082)
d_{86}: Year 1986 Dummy	1.0191^a (.2263)	1.0938^a (.2367)	1.1394^a (.2406)	1.0758^a (.2408)	1.1231^a (.2449)	1.1182^a (.2451)	1.1744^a (.2456)
d_{87}: Year 1987 Dummy	.7042^a (.2330)	.7911^a (.2431)	.8364^a (.2468)	.7397^a (.2481)	.7866^a (.2521)	.7804^a (.2522)	.8217^a (.2526)
d_{88}: Year 1988 Dummy	.8468^a (.2268)	.9428^a (.2371)	.9880^a (.2410)	.9369^a (.2407)	.9835^a (.2448)	1.0048^a (.2452)	1.0109^a (.2454)
d_{89}: Year 1989 Dummy	.6786^a (.2305)	.7250^a (.2424)	.7697^a (.2462)	.7211^a (.2459)	.7674^a (.2499)	.7873^a (.2503)	.7918^a (.2504)
d_{90}: Year 1990 Dummy	.9969^a (.2222)	1.0229^a (.2346)	1.0675^a (.2385)	1.0272^a (.2383)	1.0734^a (.2425)	1.0896^a (.2427)	1.0937^a (.2428)
d_{91}: Year 1991 Dummy	1.1119^a (.2219)	1.1996^a (.2329)	1.2444^a (.2368)	1.1986^a (.2365)	1.2450^a (.2407)	1.2546^a (.2409)	1.2602^a (.2409)
d_{92}: Year 1992 Dummy	.9475^a (.2251)	1.0577^a (.2354)	1.1019^a (.2393)	1.0403^a (.2393)	1.0861^a (.2435)	1.0983^a (.2437)	1.0909^a (.2437)
d_{93}: Year 1993 Dummy	.9620^a (.2244)	.9893^a (.2372)	1.0334^a (.2411)	.9633^a (.2417)	1.0090^a (.2457)	1.0147^a (.2459)	1.0261 (.2460)
d_{94}: Year 1994 Dummy	.7395^a (.2323)	.7331^a (.2467)	.7575^a (.2510)	.7553^a (.2502)	.7814^a (.2549)	.7852^a (.2549)	.8095^a (.2550)
d_{95}: Year 1995 Dummy	-	-	-	-	-	-	-