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Managed care competition and the adoption of hospital technology: The case of cardiac catheterization ☆

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ABSTRACT

The 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 and 1995. Results show that a hospital is less likely to adopt the technology if HMO market penetration increases but more likely to adopt if HMO competition increases. Further, the latter effect is non-linear in the number of adopters. In markets where fewer than a critical number of neighboring hospitals have already adopted, the probability of adoption increases with the number of HMOs, but in markets where more than the critical number of neighbors have already adopted, the probability of adoption decreases with the number of HMOs. 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.

1. Introduction

How does the change in competition among health maintenance organizations (HMOs) affect diffusion of technology among hospitals? Changes in health care technologies have often been cited as the main reason for rising health care costs (Newhouse, 1992). Managed care organizations, or HMOs more specifically, are believed to be the market based response to the earlier cost-plus reimbursement mechanisms that lead to excessive investment in technologies by competing hospitals.[1] Having more patients insured under HMO contracts enhances the bargaining power of third party payers and acts as a countervailing power against the excesses of hospital competition. However, the empirical case for managed care as a check on the medical arms race (MAR) is weak and with mixed results. In particular, the literature blurs the distinction between the growth of HMO penetration, i.e., with more members, the HMOs enjoy stronger bargaining power in negotiation rates with hospitals, and the effect of competition among HMOs. More recently, the managed care industry is being transformed and HMOs are themselves facing intense local competition (the average number of HMOs per market increased from 4.6 to 9.9 between 1985 and 1995). With greater number of HMOs to choose from, the impetus for reining in the MAR may be lost as HMOs vie for patients along price and non-price competition by offering access to more technology rich hospitals. The opposing effects of penetration and competition among HMOs, and their implications for the diffusion of technologies in hospitals are the focus of this paper.

The HMO–hospital relationship differs from typical vertical relations in that HMOs intermediate competing platforms with network externalities that patients and hospitals choose. Specifically, in the standard language of platforms and two-sided markets, enrollees and hospitals form the two sides, and the HMO is an intermediary firm that offers a menu of health care plans (platforms). The intermediary firm (HMO) charges a different price on each side of the market — a positive price to enrollees (a premium) and a negative price to the hospitals (a payment for services). Further, the enrollees enjoy a higher utility if the HMO contracts with more hospitals with

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[1] An HMO plan entails a capitation payment to providers and where the enrollees are assigned a primary care physician (PCP) who may then refer them for further treatment to a preselected group of providers (hospitals or specialists). Thus, the HMO need not be a vertically integrated insurance and service provider firm. There is a large variety of different types of managed care organizations (MCOs), consisting of HMOs, Preferred Provider Organizations (PPOs), Independent Practice Associations (IPAs) etc. Even though the term HMO has become almost synonymous with any type of MCO, I stick to the term HMO since good quality and geographically detailed data over the study period is available only for HMOs and these were the most prevalent form of managed care activity during the study time period.

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the technology (a network externality for the enrollees) while the hospitals obtain larger total revenue (from the HMO) if the contracting HMO has more enrollees. Thus, the platform provider's problem is to offer either only a single plan to all enrollees, or to offer differentiated (two) plans and let the enrollees self-select into a higher premium plan with access to all hospitals in the network with the technology and a lower premium plan with restricted access to hospitals with technology. In the current context, the emergence of multiple plans implies that HMOs rationalize the adoption of technology by hospitals rather than discourage the adoption by all hospitals as implied by the literature on HMO penetration.

For instance, a result established by Ambrus and Argenziano (2006, p. 11–12) is that in the presence of heterogeneous consumers, a monopolist platform provider (HMO) will always choose to setup two asymmetric platforms, one larger and cheaper on one side of the market (low premium and many enrollees) and the other larger and cheaper on the other side of the market (smaller discounts from many hospitals) as long as the incremental utilities resulting from a given increase in the number of consumers on the opposite side are uniformly bounded by a positive constant. This requirement is met if consumers have a diminishing marginal positive value in the choice of service providers.[2] Hence, in HMO monopoly markets, the HMO offers differentiated products and contracts with both, hospitals with the technology as well as those without it, precisely because those that have not yet adopted, offer a greater value to the platform provider by not adopting the technology. By contrast, in the HMO duopoly markets, one HMO's network is larger and cheaper for the enrollees while the other HMO's network is larger and cheaper for the hospitals. Thus, the effect of HMO competition on technology adoption can be understood as an application of the effect of the number of platform providers on the emergence of multiple platforms, i.e., hospitals with and without the technology (for more examples, see Ambrus and Argenziano, 2006).

Baker (2001) and Baker and Phibbs (2002) have argued that managed care organizations have an elastic demand and they are able to bargain aggressively and obtain a lower price per service for their enrollees. Thus, as HMO penetration increases, the expected profitability of the high marginal cost technology decreases for the price discriminating hospitals, which in turn delays the adoption of that technology. Consistent with their explanation, I find that the probability of adoption of cardiac catheterization laboratories (cathlabs) decreases with HMO penetration. However, I also find that the probability of adoption may either increase or decrease with the number of HMOs, depending on whether less or more than a critical number of neighboring hospitals have already adopted the cathlabs. Thus, the combined effect of HMO competition and penetration could be ambiguous (and small) since each has a countervailing effect on the adoption of technology, at least in the early stages of adoption.

I explain the threshold effect in the HMO competition on technology adoption by extending Sorensen's (2003) bargaining model between HMOs and hospitals. HMOs solicit bids from hospitals and contract with the lowest bidder. The equilibrium discount offered by a bidding hospital is a decreasing function of the number of other pre-existing hospitals in the HMOs' network and an increasing function of the HMOs' ability to channel enrollees to network hospitals (henceforth, the number of hospitals in an HMO's network is referred to as the size of the network). In turn, an HMO's ability to prevent enrollees from using non-network hospitals increases if it has more network hospitals. Thus, changing the size of the pre-existing network creates a trade-off in the discount offered by the bidding hospitals: A bidding hospital would offer a larger discount if the size of the pre-existing network is small, but a smaller pre-existing network also implies that an HMO's ability to channel enrollees to in-network hospitals is weak and hence the discount may not be large. Whether hospitals offer a small or large discount depends on the relative values of the size of the pre-existing network and the HMOs ability to prevent leakage from the network. Finally, as HMO competition intensifies, HMOs offer greater choice to enrollees by offering access to larger networks of hospitals. Consequently, the discount offered by bidding hospitals decreases (increases) with the number of HMOs if the size of the network is less than (greater than) a threshold. Intuitively, if the existing network is small, then hospitals offer decreasing discounts in the number of HMOs because the bidding hospital loses a larger fraction of HMO enrollees to other network hospitals relative to the gain that comes with more enrollees using network hospitals.

Since the discount offered by a hospital changes its expected profitability, and hence the timing of adoption of expensive technologies, I estimate a reduced form hazard rate model for the adoption of cathlabs in U.S. hospitals.[3] The next section briefly reviews some relevant studies on HMO penetration and technology adoption and extends the discussion to the role of HMO competition. Section 3 specifies the empirical model and Section 4 has the results. This is followed by a brief section on marginal probabilities as a function of the number of HMOs. The final section provides a discussion and summary of the results.

2. Hospitals' adoption decision and the role of HMOs

2.1. Prior literature

There is a substantial literature that has focused on market structure — specifically hospital competition — and technology adoption. Rapoport (1978) found that hospitals in more competitive markets tended to adopt new innovations faster, while Luft et al. (1986) found that a hospital is more likely to offer a specialized service if other hospitals in the market also offer a similar service (at least for some services). Dranove et al. (1992) report similar results but find that the MAR effect is economically small and can be explained by more conventional factors such as the extent of the market. Hamilton and McManus (2005) investigate the diffusion of a new injection technology (intracytoplasmic sperm) in fertility clinics and report that clinics in competitive markets offered the technology earlier than in monopolies. Others have focused on strategic interactions on the timing of adoption.[4] For instance, Vogt (1998) investigates the adoption of MRI in duopoly hospital markets and finds evidence consistent with preemptive adoption models while Schmidt-Dengler (2006), who also studies the adoption of MRIs in small hospital markets, finds that business-stealing effect is relatively more important than preemption.[5]

Related literature has focused on the role of insurance on technology diffusion. Baumgardner (1991) links the changes in marginal valuation (to consumers) of the introduction of a technology (in a hospital) to the type of insurance contract. On the basis of this assumption he provides testable specifications that the probability 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

[2] By diminishing marginal value of choice I mean the following: Holding price (premium) and other things constant, consumers prefer to enroll in HMOs that provide access to more hospitals (with technology) but this effect diminishes if each HMO contracts with a sufficiently large number of hospitals.

[3] For a link between a firm's expected profitability from adoption at time t and the hazard rate models, see Rose and Joskow (1990) or Reinganum (1989).

[4] Often these papers test assumptions or predictions of theoretical models of adoption in the IO literature, e.g. Reinganum (1981); Fudenberg and Tirole (1985).

[5] There is also a large literature on regulations (e.g. CON laws, introduction of PPS) and adoption of technology and is not reviewed here. See Acemoglu and Finkelstein (2006), Sloan et al. (1988), Joskow (1981), Sloan and Steinwald (1980), Salkever and Bice (1976).

equilibrium number of (single service) health providers with changes in HMO activity. Both of these models suggest that at least for some technologies, an increase in HMO penetration will discourage technology adoption by hospitals. Consistent with these predictions, Cutler and McClellan (1996) found that hospitals in areas with high HMO enrollment are less likely to adopt angioplasty. Similarly, Baker (2001) and Baker and Phibbs (2002) estimate models for the adoption of magnetic resonance imaging and neonatal intensive care units respectively and find that in both cases the increases in HMO penetration are associated with a decrease in the adoption hazard. However, Baker and Spetz (1999) investigate several technologies and report mixed findings.

Baker and Phibbs (2002) argue that managed care organizations have the ability to change both the price and volume of services provided by hospitals, which in turn change the expected profitability of these services and hence the time to adoption (the implicit assumption is that a hospital will adopt a new technology when the discounted expected profit at a given time from adopting the technology is greater than from not adopting it). However, in all of the papers cited above, an increase in managed care activity is synonymous with an increase in managed care penetration (i.e. percent of population enrolled in managed care plans) and does not account for competition among managed care organizations. Pauly (1998) has argued that concentration in the insurance market can lead to more price competition in hospital markets. It is important to recognize that penetration and competition (within managed care firms) are not two faces of the same coin, and could have very different effects on hospital profitability vis-a-vis their relative bargaining power with the hospitals. More generally, the mixed results on the effect of HMO penetration on technology adoption (see Baker and Spetz, 1999) could be due to the omission of HMO competition or their relative bargaining power. For instance, Gaynor and Haas-Wilson (1999) note that the merger wave of 1990s, both among the providers and insurers, was in part driven by attempts to strengthen their bargaining positions. In this paper, I explicitly recognize the competition effect (as separate from the penetration effect) and show that HMO penetration and competition have opposite effects on adoption decisions by hospitals when there are few hospitals with the technology. Consistent with my results, Shen et al. (2008) find that HMO penetration and concentration have distinct effects on hospital revenue per patient, but more importantly, hospital revenue growth is slower in markets where HMOs are concentrated but hospitals are competitive.

2.2. Extension to the number of HMOs

The effects of HMO competition on the price and volume of services provided by hospitals follow naturally from this literature. The basic intuition is that when there are multiple HMOs in an area, then no one HMO may have substantial bargaining power to obtain large discounts from hospitals.

2.2.1. Price

Consider the price effect. Since HMOs' demand is elastic (Welch, 1986) and they bargain with providers for a lower price per service for their enrollees, a given HMO can do this effectively if it has a relatively large market share of the HMO market. If, on the other hand, the number of HMOs is also relatively large, such that each individual HMO has only a very small share of the market, then getting large price discounts from the hospitals may not be possible. This would be true even if an individual HMO's threat to channel patients to alternative hospitals is credible since the total enrollment of the HMO is small. Thus, while the threat is credible, it is ineffectual. This in turn implies that for a hospital facing a given level of aggregate HMO penetration, expected discounted profits from the adoption of a technology are likely to be higher if the HMO enrollees are distributed across many firms than when the HMO market is dominated by only a handful of firms.

2.2.2. Volume

Changes in the number of HMOs can change the hospitals' expected discounted profits via changes in volume of services provided by hospitals. While each HMO may use mechanisms to induce network physicians to lower the use of expensive technologies, their ability to do so may be limited if there are many HMOs competing with each other to sign enrollees and physicians into their network. If the number of HMOs increases, it may induce greater non-price competition among them. 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 a given time will be greater if there are more HMOs in the market than if there were a few. Additionally, there may be a very limited, or even no change in the prescribing behavior of the network physicians implying a lack of reduction of volume even among the FFS patients seen by the same physicians.

2.2.3. Non-linearities

HMOs compete with each other for enrollees by offering lower premiums and/or access to more service providers with technology. It is possible that the impact of the number of HMOs on the adoption of technology by hospitals will be non-linear (or more accurately, have a threshold effect): If fewer than a critical number have adopted that technology, then the probability of adoption will increase with the number of HMOs but once it is relatively well diffused (more than a critical number have adopted) the probability will decrease with more HMOs. I describe below one specific model from the literature, which, with some modifications, generates this non-linearity.[6]

Sorensen (2003) describes a simple bargaining model with one HMO and two perfect substitute hospitals where the HMO's enrollees are expected to require S units of hospital service and the HMO solicits bids from two hospitals. He shows that the symmetric equilibrium bidding strategy of each hospital is $d_i^* = (1-c_i)(1-(1/2\gamma))$ where the price of a unit of hospital service is normalized to 1 and where d_i and c_i is the discount offered by hospital i and its unit cost respectively (where $c_i \in [0, 1]$). In his model, a parameter γ (where $1/2 \le \gamma \le 1$), is exogenous and is the degree to which the insurer can channel its patients to a given hospital ($\gamma = 1/2$ means that the HMO has no ability to do so and 1 means that it has full control). Thus γ is the ability of the HMO to restrict patients to the network hospital which provides γS units of service at the unit price of $1-d_i$ while the non-network hospital provides $(1-\gamma)S$ units of service at the full price of 1.

Now consider an extension to this model where there are multiple HMOs which have an existing size of network providers and who are competing for enrollees by offering not just lower premiums but also a greater choice of providers with technology. Specifically, let there be N HMOs in the market such that the jth HMO *already* has contracts with G_j number of hospitals with technology T and where its enrollees are expected to require S_j units of service from the network hospitals (the hospitals are perfect substitutes and receive $1/G_j$ fraction of the HMO's enrollees). Assume it is soliciting bids from the remaining K hospitals ($K>1$) in the market so as to enlarge its network. Each hospital offers a discount d_i and the (one) winning bidder will receive a $\gamma_j/(G_j+1)$ proportion of the HMO's total patient charges where $(G_j+1)/(G_j+K) \le \gamma_j \le 1$. As in Sorensen, γ_j is the degree to which the HMO can channel its patients to network hospitals (the lower bound implies that it has no ability to keep them restricted to network hospitals and

[6] Note, this is not the only model that can generate such a non-linearity. The purpose is to provide an economic framework and context to help understand the empirical results that follow.

the upper bound is that it has full control to keep them restricted to the new network). Equivalently, if the HMO has no control over its enrollees, then all G_j+K receive an equal share of the HMO's enrollees. Thus, the profit of the ith hospital bidding a discount d_i, conditional on adopting technology T, is given by

$$\Pi_i(d_i,c_i|T=1)=\begin{cases}(1-d_i-c_i)\dfrac{\gamma_j S_j}{G_j+1}-\alpha & \text{if } d_i>d_j\forall j\neq i\\ (1-c_i)\dfrac{\left(1-\gamma_j\right)S_j}{K-1}-\alpha & \text{otherwise}\end{cases} \tag{1}$$

where α is the fixed cost and is the same for all hospitals. Thus if hospital i wins the bid at d_i then it provides $\gamma_j S_j/(G_j+1)$ units of service at price $1-d_i$ (unit price is normalized to 1) and otherwise it services $(1-\gamma_j)S_j/(K-1)$ at full price. The ith hospital's problem is to find d_i^* such that the expected profit is maximized, i.e.,

$$\max_{d_i}\left((1-d_i-c_i)\frac{\gamma_j S_j}{G_j+1}-\alpha\right)\Pr(d_i>d^*(c_k)\forall k\neq i)+\left((1-c_i)\frac{\left(1-\gamma_j\right)S_j}{K-1}-\alpha\right)(1-\Pr(\cdot)). \tag{2}$$

The symmetric equilibrium strategy is then given by (for derivation see Appendix A)

$$d^*(c_i)=\frac{(1-c_i)}{K}\left((K-1)-\frac{\left(1-\gamma_j\right)(G_j+1)}{\gamma_j}\right) \tag{3}$$

where c_i is the unit cost of providing service, K is the number of non-network bidding hospitals and G_j is the number of existing network hospitals for HMO j. Note that if $\gamma_j=(G_j+1)/(G_j+K)$ (i.e., the HMO has no ability to require the enrollees to stay within the network) then d_i is equal to zero. Further, if $\gamma_j=1$, (i.e., the HMO has full control) then $d_i=(1-c_i)(K-1)/K$. Finally, Sorensen's results are reproduced as the special case with $G_j=0$ and $K=2$ (no pre-existing network and only 2 bidding hospitals).

In a full multi-stage game (with multiple HMOs and unrestricted entry) both the size of the network and an HMO's control parameter would be determined endogenously and be functions of the number of HMOs (i.e., $G_j=G_j(N)$ and $\gamma_j=\gamma_j(G_j(N),N)$).[7] In the absence of such a model, it is still useful to explore (via comparative statics) the implied effect of changes in the number of HMOs on the optimal bid. Thus, taking the derivative of d_i^* with respect to N gives

$$\frac{dd_i^*}{dN}=-\frac{(1-c_i)}{K}\left[(-1)\frac{(G_j+1)}{\gamma^2}\left\{\frac{\partial\gamma_j}{\partial N}+\frac{\partial\gamma_j}{\partial G_j}\frac{\partial G_j}{\partial N}\right\}+\left(\frac{1}{\gamma_j}-1\right)\frac{\partial G_j}{\partial N}\right], \tag{4}$$

where the quantity in the curly braces ($\{\cdot\}$) is the total or net change in the HMO's ability to control enrollees due to a change in the number of HMOs and is the sum of the direct effect on the control parameter of an increase in HMOs ($\partial\gamma_j/\partial N$) and an indirect effect ($(\partial\gamma_j/\partial G_j)(\partial G_j/\partial N)$) due to the intermediate change in the size of the network ($\partial G_j/\partial N$). Henceforth, let the sum, i.e., the total effect on the control parameter, be denoted by $d\gamma_j/dN$.

The partials in Eq. (4) above determine the change in the optimal discount as a function of the number of HMOs. Thus, it is necessary to make some plausible assumptions about the signs of these partials. First, suppose that as the number of HMOs increases, the size of their network also increases since enrollees value greater choice of service providers, i.e., $\partial G_j/\partial N>0$. Indeed, Capps et al. (2003) provide a model of HMO competition, where (in the limiting case of $p=mc$ for each HMO), the dominant strategy for each HMO is to contract with all hospitals in the area as service providers. Second, $\partial\gamma_j/\partial G_j>0$, i.e., an HMO's control over enrollees use of network hospitals is an increasing function of the number of hospitals in the network. Recall that γ_j is the fraction of the enrollees that use network hospitals, thus this assumption is stating that if the size of the network increases, a greater fraction would use network hospitals. In fact, in the limit that G_j increases to all existing hospitals in the market then γ_j increases to its maximum value of 1. Finally, it maybe reasonable to assume that the direct effect on the control parameter maybe decreasing in the number of HMOs i.e., $\partial\gamma_j/\partial N<0$, — ceteris paribus an increase in the number of HMOs implies a toughness of competition among them such that more of their enrollees enjoy the freedom to seek services outside of the network.

With these three assumptions in place, note that the indirect effect of an increase in HMOs on the HMO control parameter is positive $((\partial\gamma_j/\partial G_j)(\partial G_j/\partial N)>0)$ while the direct effect on the HMO control parameter is negative ($\partial\gamma_j/\partial N<0$). If the direct effect is larger, so that the total effect (sum of the two) is negative then the entire quantity in the square brackets in Eq. (4) is unambiguously positive and hence $dd_i^*/dN<0$. Put another way, if the number of HMOs increases such that the net effect on the control over enrollees to use the network hospital decreases, then the bidding hospitals offer lower discounts to join the network. If however, the direct effect is small, then the total effect will be positive and hence the first quantity in square brackets is negative and the second is positive. In that case, the overall sign of dd_i^*/dN depends on the relative magnitudes of two quantities in the brackets. Thus, we have the following conditions.

$$\frac{dd_i^*}{dN}\begin{cases}<0 & \text{if } d\gamma_j/dN<0 \text{ and for all } G_j\\ <0 & \text{if } d\gamma_j/dN>0 \text{ and } G_j<G_j^*\\ >0 & \text{if } d\gamma_j/dN>0 \text{ and } G_j>G_j^*\end{cases} \tag{5}$$

where $G_j^*=\frac{(1-\gamma_j)\gamma_j\partial G_j/\partial N}{d\gamma_j/dN}-1$.

The story is as follows. HMOs prefer to selectively contract with a few hospitals since then they get a larger discount from the bidding hospitals (see Eq. (3)). As the competition among HMOs increases, their control over the enrollees decreases (γ_j decreases) and the bidding hospitals offer a smaller discount. However, due to increased competition, HMOs also offer a greater choice of service providers (enrollees value choice). When the size of the network increases, it has two effects. Ceteris paribus, bidding hospitals offer a smaller discount (since each bidder gets a smaller fraction of the HMO's enrollees) but it also increases the control of the HMO over its enrollees (γ_j increases) and the bidding hospitals offer a larger discount (since they get a larger fraction of the enrollees). If the net change in the control of the HMO is such that it decreases with an increase in the number of HMOs ($d\gamma_j/dN<0$), hospitals bid smaller discounts and their own profitability increases. If, on the other hand, the net change in γ_j is such that it increases with the number of HMOs ($d\gamma_j/dN>0$), then whether the discount decreases or increases in N depends on the values of G_j, γ_j and the relative speeds with which they change: If the existing network is small ($G_j<G_j^*$) then hospitals offer decreasing discounts in N — because the bidding hospital loses a larger fraction of HMOs enrollees to *other in-network hospitals* (say from 1/3 to 1/4) relative to the gain that comes with more enrollees using in-network hospitals (due to larger γ_j), i.e. since the network was small, fewer HMO enrollees actually stay within the network. Alternatively, if the network is large ($G_j>G_j^*$) then hospitals offer an increasing discount in N — because the bidding hospital loses a smaller fraction of HMO enrollees to the other in-network hospitals (say from 1/9 to 1/10) relative to the gain that comes from more enrollees using in-network hospitals. Thus, if $d\gamma_j/dN>0$, then there is some critical value of G_j (correlated with N) such that when $G_j<G_j^*$ the discount offered by the hospitals decreases with the number of HMOs and the hospitals'

[7] For instance, in a multi-stage model, the second stage would be similar to as given here but the first stage would involve each HMO deciding how many hospitals to contract with and would be a function of the number of HMOs.

profitability increases, but that after G_j^* is crossed, the discount increases in N and the hospitals' profitability decreases.

Finally, the (bidding) hospitals adopt the technology when the discounted expected profit at a given point in time from adopting the technology is greater than from not adopting it. By linking changes in the hospitals' expected profitability due to adoption to the timing of adoption (see Reinganum, 1989), I estimate proportional hazard models for the adoption of one specific technology — cardiac catheterization laboratories — in U.S. hospitals.

3. Empirical specification

3.1. Cardiac catheterization

Cardiac catheterization is a procedure (indicated for patients with heart disease) during which a thin catheter is threaded into the heart through the arteries to locate and/or to open the blockages using balloons or stents.[8] 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 results from an angiogram may call for an angioplasty (formally known as PTCA) or open-heart surgery (formally known as CABG). The procedure takes place in a specialized laboratory in a hospital, called the cardiac catheterization laboratory (henceforth, cathlab).

I use the adoption of cathlabs as a test case for three reasons. First, the cathlab is an important technology and has contributed significantly to productivity gains in heart attack treatments. For instance, in the U.S., the first PTCA was performed in 1978 and over the next two decades it grew to about 40/10K population. Over the same period, the number of heart attacks has remained fairly constant (near 30 per 10K population), but the deaths resulting from heart attacks have declined at an annual rate of 2% (Gowrisankaran, 2002). Similarly, Cutler and McClellan (2001) report that the average life expectancy for elderly heart attack patients has increased by just over one year between 1984 and 1998.[9]

Second, cardiology is a lucrative business and adoption of cathlabs has been rapid.[10] Additionally, often multiple hospitals in the same market adopt the technology. 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 as more physicians to join the hospital, and through these physicians, attracts yet more patients (on a related issue, see also Hodgkin, 1996). Nonetheless, it is an expensive technology to adopt as well as an expensive procedure to perform. For instance, the adoption costs could be as high as $7M (in 1999) and the average hospital charge for an angioplasty (PTCA) in 1995 was $20,370 (American Heart Association, 1999, p. 26). Given these costs, the presence of HMOs is likely to affect the technology adoption decision by hospitals.

Third, starting in the mid 1980s, HMOs experienced a rapid growth. Between 1985 and 1995, the average number of HMOs per area increased from 4 to 9 and HMO penetration increased from 7% to 20%. Over the same period, the number of hospitals with cathlabs grew from 18% to about 35%, making estimation feasible. Additionally, during this study period, cathlabs were mainly a hospital technology, i.e., there were no free standing catheterization laboratories and hence the need to collect additional data (to account for confounding affects due to competition from single service providers) was eliminated. Several other hospital technologies diffused either before or after the HMO growth era, or were available outside of the hospital as well.

Thus, 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 the complementary log–log form of the hazard as

$$\lambda_{ij} = 1 - \exp\left\{-\exp\left(x_{ij}'\beta + \lambda_j\right)\right\} \tag{6}$$

where x_{ij} include measures of HMO activity, hospital specific characteristics and other relevant local area characteristics. Specifically, x_2 and x_3 are HMO penetration and number of HMOs in the hospital's market and x_4 and x_5 are total number of other hospitals and number of hospitals that have *already* adopted the cathlabs by the previous period. Prior literature has often measured HMO activity at the Health Services Area (HSA) level — an HSA is a cluster of counties — in part because HMOs compete for enrollees over relatively large geographic areas.[11] Following the literature, I also measure HMO penetration and number of HMOs (x_2 and x_3) at the HSA level. Whereas HMOs may compete over relatively large geographic areas, non-specialty hospitals mostly attract patients from local areas (Gaynor and Vogt, 2003). Thus, rather than measure x_4 and x_5 at the HSA level, I computed these variables based on a 24-mile radius using the hospitals' ZIP codes. Specifically, for each hospital, x_4 counts the number of other hospitals within a 24-mile radius and x_5 counts how many of these neighboring hospitals had already adopted cathlabs by the previous period. The 24-mile criterion for measuring the characteristics of a local hospital market, while somewhat arbitrary, has often been used in the medical arms race literature (Luft et al., 1986; Robinson and Luft, 1987; Robinson et al., 1988) and will be used here as well to facilitate comparison of results with prior research.

The conditional probability itself is not linear in the covariates and could increase or decrease with x_k (k=2, 3) depending on the value of other covariates. For instance, based on the discussion in Section 2, the change in conditional probability of adoption with respect to x_3, i.e., $\partial\lambda_{ij}/\partial x_{ij3}$ could be positive or negative depending upon how many hospitals have already adopted the technology i.e., whether x_5 is small or large (henceforth the partial is referred to as the marginal probability). Thus, the specification also includes interaction terms x_2x_5 and x_3x_5. Finally, based on the earlier discussion, I state the following hypotheses: $\frac{\partial\lambda_{ij}}{\partial x_{2ij}}<0$ for all (reasonable) values of x_5. But $\frac{\partial\lambda_{ij}}{\partial x_{3ij}}>0$ if $x_5<x_5^*$ (technology still diffusing) and $\frac{\partial\lambda_{ij}}{\partial x_{3ij}}<0$ if $x_5>x_5^*$ (technology already diffused). The first hypothesis follows from the findings reported in prior literature that the probability of adoption decreases with HMO penetration. The second and third follow from my discussion on the threshold effect in hospital profitability as a function of the number of HMOs (i.e., that $\mathrm{d}d_i^*/\mathrm{d}N<0$ if $G_j<G_j^*$ and $\mathrm{d}d_i^*/\mathrm{d}N>0$ if $G_j>G_j^*$ when $\mathrm{d}\gamma_j/\mathrm{d}N>0$).

3.2. Data on cathlabs

The data on the 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

[8] 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 the 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.

[9] Note that not all the gains can be apportioned to procedures performed in a cathlab. For instance, some gains are due to the use of other technologies e.g. clot-busting drugs, ACE inhibitors and changes in lifestyles. Heidenreich and McClellan (2001) associate 34% of the increase in life expectancy after a heart attack due to increased use of aspirin (over 1975–1995) and a further 17% due to increase in use of clot-busting drugs.

[10] 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%.

[11] Briefly, an HSA as a group of counties such that the flow of hospital patients across HSAs is minimized across its boundaries. For details on grouping algorithm, see Makuc et al. (1991a,b).

care hospitals and has a response rate of about 90%. 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 baseline sample was constructed using all non-federal short-term general community hospitals with non-missing information on cathlabs and on the covariates for each of these years. In 1985, there were 5169 hospitals in the sample of which 775 (15%) had already adopted cathlabs either during that year or in a prior year. Thus, for the baseline analysis, the sample consisted of 4394 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 (along with information on its covariates) could not be followed for all the years until 1995, then it was treated as censored. For instance, 103 hospitals were considered censored at the end of 1986 because either the hospital ID itself was not present in 1987–1995 AHA files (merged or closed down) or because information on covariates was missing/miscoded.

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 additional 746 (about 37%) by the end of 1995 (see Table 1). The fraction 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.

Table 1
Summary of catheterization laboratory adoption data

Adoptions by Short-Term General Community Hospitals between 1986 to 1995[a]						
Year	Hospitals at risk	Cathlab adoptions (exits)	Censored hospitals[b]	New entries[c]	Kaplan–Meir surviver function $\hat{s}_t$	Cumulative adoption probability $1-\hat{s}_t$
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.

[a] In our sample, 775 hospitals had already adopted cathlabs by 1985. Excluding these, 4394 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 4553 unique hospitals that were observed between 1986 and 1995.

[b] Censored hospitals are those 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.

[c] 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.

3.3. Data on HMOs and other covariates

The HMO data, provided by Wholey et al. (1995), gives measures of HMO penetration and the number of *unique* HMOs in each HSA and is summarized in Table 2.[12] Average penetration increased from 7.8% to 20.4% while the number of HMOs per HSA increased from 4.63 to 9.9. In addition to measures of HMO activity and the number of neighboring hospitals (total and those already with a cathlab), 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 obtained from the AHA files.

Data on other control variables (population, population over 65, income per capita and AFDC dollars per capita) and state level variables (Certificate of Need (CON) laws, the year 10% of farms in the state adopted tractors) were obtained from Area Resource File (1996 CD) and published reports on state laws. The data on these covariates is summarized in Table 2.[13]

4. Estimates from hazard rate models

There is a significant amount of variation in hospital and area characteristics of these hospitals. For instance, in the full sample (obs=35,834), while the mean value of HMO penetration is 8.9% (s.e.=.227), the actual values range from 0 to 70% in the HSA of the hospital. Similarly, for each hospital there are on average about 11 neighboring hospitals (s.e.=.162) within a 24-mile radius, the actual number ranges from 0 (in rural areas) to about 134 hospitals (in some very dense areas such as those in Los Angeles, 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 the hazard function 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. The main results are summarized in Table 3 and are labeled '1' through '7'. 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 the number of neighbors (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 et al. (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. The coefficient on HMO penetration (x_2) is negative and statistically significant and is consistent with results reported in Baker (2001) and Baker and Phibbs (2002). However, the coefficient on the number of HMOs (x_3) is positive and significant indicating that as the number of HMOs increases, the adoption hazard increases.

The specification also includes interaction terms between x_5 and the HMO variables. The interaction term with HMO penetration ($x_2 \cdot x_5$) is not statistically significant but the interaction term with the number of HMOs is negative and statistically significant ($x_3 \cdot x_5$). Further, this interaction term is about one order of magnitude smaller than the

[12] Their data set is based on InterStudy Censuses (1985 to 1995), InterStudy Reports on areas served by HMOs, and annual National Directories of HMOs (1988 to 1991) produced by Group Health Association of America. For details see Wholey et al. (1995).

[13] The data on population, income and AFDC is from the county of the hospital. Ideally, these variables should be measured at the local level (i.e., 24-mile radius of the hospital) but such a dataset is not available. Also, the results are not sensitive to HSA level values versus county level values of these variables.

Table 2
Descriptive statistics

Year	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995
Average # of HMOs	4.63	6.37	7.28	9.37	9.09	8.92	8.90	9.15	8.85	8.81	9.98
Average penetration (%)	7.83	9.73	11.55	13.05	13.68	14.36	14.95	15.88	16.29	17.91	20.37

Note: Data is weighted by HSA population. Thus, the average HSA penetration is also the penetration level for the entire U.S. for the year as well and the average number of HMOs is the average number of unique HMOs per HSA.

	Obs=35,834		Obs=31,160	
	Mean	Standard error	Mean	Standard error
x_2: HMO penetration	8.902	0.227	9.180	0.214
x_3: # of HMOs	5.017	0.162	5.028	0.140
x_4: # of neighbors	10.854	0.648	8.699	0.394
x_5: neighbors w./cathlabs last year	4.066	0.265	3.290	0.177
x_2:x_5: (HMO penetration)×(neighbors w./cathlabs)	79.531	7.432	64.844	4.930
x_3:x_5: (#HMOs)×(neighbors w./cathlabs)	57.792	5.781	43.562	3.883
x_8: 1/0 dummy — 1 if CON law in state-year	0.733	0.008	0.742	0.007
x_9: 1/0 dummy — 1 if located in a rural county	0.086	0.002	.	.
x_{10}: year 10% of farms adopted tractors	1929.7	0.151	1930.1	0.141
x_{11}: per capita income (1982–84 constant 1000's $)	12.313	0.056	12.236	0.051
x_{12}: per capita AFDC $ (1982–84 constant 1000's $)	43.445	7.285	33.076	4.617
x_{13}: population over 65 (in 100,000s)	0.470	0.049	0.413	0.033
x_{14}: square of population over 65 (in 100,000s)	1.892	0.400	1.388	0.252
x_{15}: total population(in 100,000s)	4.109	0.495	3.545	0.324
x_{16}: 1/0 dummy — 1 if for-profit	0.125	0.005	0.126	0.004
x_{17}: 1/0 dummy — 1 if medical school affiliated	0.060	0.002	0.057	0.002

Note 1: Standard error of the mean is clustered where clusters are over HSAs and years.
Note 2: The statistics are from two samples.
Obs=35,834: Pooled hospital-year observations (1986–1995) for hospitals 'at risk' beginning of 1986.
Obs=31,160: Same as above, except observations on new hospitals, those in rural areas, and those from very dense areas have been removed.

coefficient on the number of HMOs. In the lower part of Table 3, I provide estimates of the marginal probabilities ($\partial\lambda_{ij}/\partial x_k$ for x_k=x_2 and x_3) computed at the sample mean.[14] 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.

4.1. Unobserved heterogeneity

4.1.1. New hospitals

Table 1 shows that 159 new hospitals entered the observation set after 1986. These 'new' hospitals were either truly new hospitals, old hospitals with no observations in the AHA files for the previous years, or possibly the result of mergers. It is possible that these new hospitals could be (partially) driving 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 3, 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.

Table 1 also shows that there were several hospitals that exited the observation set prior to 1995. For instance, 100 hospitals could not be followed 1990 onwards in the AHA dataset and had not adopted the cathlabs by 1989. In the usual language of time to event models, they are considered censored observations and only contribute to the likelihood function until they are censored. As such no special treatment for these hospitals is needed as long as the censoring mechanism itself is non-informative. But if the censoring itself is primarily due to merger/closing, which itself is correlated with probability of adoption, then the usual concerns about sample selection apply. An example would be if the censored observations are from hospitals for whom a large number of neighbors have already adopted the cathlabs, and the non-adopters exit the market since they cannot get favorable contracts from HMOs. To check this, I re-estimated the model by also excluding an additional 1232 hospitals (=103+120+…+202) from the risk set. The results were virtually the same as those reported in column 2 (not shown) and hence in the rest of the specifications, I do not exclude these additional 1232 hospitals (so as not to reduce the sample size too much).

4.1.2. Hospitals in rural/dense areas

Since it is possible that the hospitals in rural or very dense areas behave differently from 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 in rural counties, column 4 drops observations from areas where hospital markets are dense, specifically if a hospital has more than 100 neighbors, and column 5 drops both type of observations. In all three specifications, the results are virtually the same as 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. For instance, by excluding observations from the rural areas, the marginal probability with respect to HMO penetration changes from −.00018 to about −.00024 and the marginal with respect to number of HMOs changes from about .00041 to .00054. 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).

4.1.3. 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. Certificate of Need (CON) laws are one such

[14] Marginals were computed at the sample mean (i.e. at $X_i=\bar{X}$) as follows: Let Λ be the transformation such that $\Lambda(I)=1-\exp(-\exp(I))$ where $I=X\beta$ and X is the full data matrix then $\frac{\partial\lambda_{ij}}{\partial x_k}=\frac{\partial\Lambda}{\partial I}\cdot\frac{\partial I}{\partial x_k}$ where $\frac{\partial\Lambda}{\partial I}=\exp(I-\exp(I))$. The significance is established by the delta method. For instance, for the marginal wrt number of HMOs (x_k=x_3) the computation is as follows: Let $h\left(\hat{\beta}\right)=\frac{\partial\lambda_{ij}}{\partial x_3}$. Then $h\left(\hat{\beta}\right)=\frac{\partial\lambda_{ij}}{\partial x_3}=F'(I)\partial I/\partial x_3=\exp(-\exp(I))\exp(I)(\partial I/\partial x_3)$ where $I=\widehat{\beta^T}\,\bar{X}$ and the s.e. is the square root of the leading diagonal $\nabla^T h\hat{V}_c\nabla h$ where ∇h is a $k\times1$ vector with the jth row given by $F''(\cdot)\frac{\partial I}{\partial x_3}\frac{\partial I}{\partial\beta_j}+F'(\cdot)\frac{\partial^2 I}{\partial\beta_j\partial x_3}$ and where $F''(\cdot)=F'(\cdot)(1-\exp(I))$ and $\hat{V}_c$ is the estimated (clustered) variance–covariance matrix of $\hat{\beta}$.

Table 3
Discrete time hazard rate estimation

	Specifications						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variable	Selected coefficients and standard errors[1]						
x_2: HMO penetration	−.0139[b]	−.0145[b]	−.0145 [b]	−.0119	−.0119	−.0104	−.0039
	(.0071)	(.0074)	(.0074)	(.0074)	(.0074)	(.0074)	(.0075)
x_3: # of HMOs	.0456[a]	.0466[a]	.0465[a]	.0428[a]	.0427[a]	.0406[a]	.0377[a]
	(.0126)	(.0130)	(.0130)	(.0134)	(.0134)	(.0132)	(.0137)
x_4: # of neighbors	−.0316[a]	−.0334[a]	−.0335[a]	−.0280[a]	−.0282[a]	−.0287[a]	−.0296[a]
	(.0065)	(.0067)	(.0067)	(.0072)	(.0072)	(.0072)	(.0072)
x_5: neighbors w./cathlabs last year	.1126[a]	.1200[a]	.1202[a]	.1323[a]	.1324[a]	.1301[a]	.1221[a]
	(.0194)	(.0201)	(.0201)	(.0200)	(.0200)	(.0201)	(.0202)
x_2:x_5: (HMO penetration)×(neighbors w./cathlabs)	.0006	.0007	.0007	−.0000	−.0000	.0001	−.0002
	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
x_3:x_5: (#HMOs)× (neighbors w./cathlabs)	−.0047[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0040[a]
	(.0008)	(.0008)	(.0008)	(.0009)	(.0009)	(.0009)	(.0009)
x_8: CON law dummy. 1 if law in effect in state-year	–	–	–	–	–	.2322[b]	.1010
						(.1083)	(.1103)
x_9: year 10% of farms adopted tractors	–	–	–	–	–	–	.0296[a]
							(.0057)
x_{10}: rural area dummy. 1 if rural area	−3.1564[a]	−3.1238[a]	–	−3.1053[a]	–	–	–
	(.7095)	(.7096)		(.7098)			
Marginal with respect to:	Selected marginals $\left(\frac{\partial \lambda_{ij}}{\partial x_k}\right)$ and standard errors						
x_2: HMO penetration	−.00018[b]	−.00018[b]	−.00023[b]	−.00018[b]	−.00024[b]	−.00021[c]	−.00009
	(.00010)	(.00010)	(.00013)	(.00010)	(.00013)	(.00013)	(.00013)
x_3: # of HMOs	.00041[b]	.00041[b]	.00050[b]	.00042[a]	.00054[a]	.00049[b]	.00048[b]
	(.00018)	(.00018)	(.00024)	(.00018)	(.00024)	(.00024)	(.00024)
Exclude new hospital obs?[2]	x	✓	✓	✓	✓	✓	✓
Exclude rural area obs?[3]	x	x	✓	x	✓	✓	✓
Exclude dense area obs?[4]	x	x	x	✓	✓	✓	✓
# of hospitals at 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. Clustered s.e. are in parenthesis.
Note 1 (other variables — See Appendix B): All specifications include 10 time dummies (i.e., baseline hazard parameters) and 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 are given in Appendix B.
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 if it is not adjacent to a metro area and if no city within the county has population greater than 2500. For these counties, the total population varies from 1300 to about 36,000.
Note 4 (dense areas observations): These included hospitals in the following 7 MSAs/PMSAs: Bergen–Passaic, Newark and Jersey City in NJ Los Angeles–Long Beach and Orange Cnty in CA and Nassau–Suffolk and New York City in NY.

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. 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 intangible 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 the (Putnum) Social Capital index.[15] 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 an omitted variable bias.[16] 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 intangible 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 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 computers in 1993, (4) Putnum Social Capital Index and, (5) Putnam Education Index.[17] All of these variables are highly

[15] The index (by Putnam, 2000) consists of an aggregated value of sub-indexes ranging from questions about life styles of the individuals to counts of non-profit organizations in the area/state. For details see http://www.bowlingalone.com/data.php3.

[16] Alternatively, in addition to time dummies already in the model, we can include state level dummies. However, such a strategy was not feasible in the current context, since it divides a total of 706 binary 'events' over 50×10 cells.

[17] Following Griliches (1957), the year 10% of farms in the state adopted tractors was computed by Skinner and Staiger (2005). I am in debt to Doug Staiger for providing data on all of the above mentioned variables, including data on the Putnum indicators.

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.

4.2. Robustness

In all the seven specifications, the marginal probability with respect to the number of HMOs at the sample mean is positive, i.e., at the sample mean a small increase in the 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 statistically 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 3).

In addition to the variation in specifications above, I also estimated the hazard rate using (1) logit specification (instead of the complementary log–log), (2) measuring HMO variables at the county level (instead of HSAs), and (3) alternative measures of HMO competition, specifically either the Herfindahl index, its inverse, or number of HMOs per capita (instead of number of HMOs). In all cases the results were qualitatively similar (and are available from the author upon request).

4.3. Endogeneity

It is possible that some unobserved local market factors that may be changing over time affect both, 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. Nonetheless, in this section, I treat the HMO variables (x_2, x_3 and their interactions with x_5) as potentially endogenous. Additionally, it is possible that x_5 by itself is also endogenous. Note that x_5 does not cause a simultaneity bias per se, since it is equal to the number of hospitals that had adopted catlabs by the *previous* period, i.e., is a lagged variable in the specifications. However, it may still lead to biased estimates due to other reasons — specifically a hospital may adopt technology to discourage or encourage future adoptions by other hospitals — in which case it would be correlated with the censoring mechanism. I already considered this possibility earlier by comparing hazard rate results from the full sample with those where I excluded 1232 hospitals that closed prior to adopting cathlabs (see discussion in Section 4.1.1). Since the estimates did not change, it is unlikely that x_5 is endogenous. However, in this section, I use the instrumental variables approach and account for possible endogeneity of this variable as well.

Due to the qualitative nature of some of the right hand side variables of interest (number of HMOs, number of neighbors with cathlabs etc.), I first re-estimate the hazard model as a linear probability model and compare it with the results in Table 3. Next, I use the GMM-IV methods on the linear probability model (treating the number of HMOs and neighbors with cathlabs as quantitative variables) and test how much the estimated coefficients change if the HMO variables (and x_5) are endogenous. While not conclusive, however, if in the linear probability models endogeneity is not a serious issue (say on the basis of the Hausman test), then it is *indicative* that the results in Table 3 are not seriously biased on account of endogeneity of these variables.[18]

4.3.1. Instruments

Large employers are more likely than small employers to offer their employees a choice of insurance plans, including the choice to enroll in HMOs. This is partly because a federal law mandates that firms with more than 25 employees must offer their employees the choice to join an HMO, providing that the firm offers an insurance plan and there is an HMO in the market that wishes to be included. This suggests that markets with large employers will be more attractive to HMO entry making it a relevant instrument. Dranove et al. (2003) used a variation of the later variable in a model that predicts the number of HMOs in an area and found it to be significant. Additionally, it would also be a valid instrument as long as large employers do not directly influence provider behavior independently of the effect of HMOs. In a related study on number of mammography providers in an area, Baker and Brown (1997, 1999) report that the number of large businesses as an instrument for HMO variables satisfied the exclusion restrictions. Thus, my first instrument is the number of firms with 100 or more employees per capita in the HSA (henceforth z_1).

Independent of the effect of large employers on HMOs, several state regulations may also alter the incentives for HMOs to enter in local markets or their ability to expand in these markets. For instance, the enactment of "any willing provider" and "freedom of choice" laws (henceforth AWP or FOC), which are often lobbied by providers (hospitals, physicians and pharmacies) may be seen as preemptive strikes to prevent or delay the emergence of selective contracting in their markets. The AWP laws require HMOs to accept any provider in their network who is willing to abide by the rules of a standard contract with other providers. This implies that an HMO would have a limited ability to extract large discounts from providers in exchange for a large/concentrated volume which in turn would restrict HMO growth in these markets. One study (Sheils et al., 1995) estimates that the AWP laws resulted in 6.9% slower increase in HMO enrollment over the period 1985–1994. The FOC laws would have a similar impact on HMOs, however, the mechanism is different. The FOC laws require HMOs to allow patients to go outside the network to obtain covered services from non-network providers. The main difference is that the managed care firm may pay the provider a price typically below the price negotiated with network providers, but the patient is required to make a larger copayment. Additionally, the FOC law sometimes allows the new provider to balance-bill the patient. The FOC law primarily effects the HMO growth via price elasticity of the out-of-pocket payments. Thus, AWP and FOC laws restrict HMOs in different ways and the latter may be viewed as a 'consolation prize' for proponents (hospitals, physicians, pharmacies) who do not have a strong enough lobby to help enact AWP laws (see Ohsfeldt et al., 1998). I use FOC and AWP laws as second and third instruments respectively (z_2 and z_3).[19] Additionally, large firms which can choose to self-insure are sometimes exempt from FOC/AWP laws. Thus, two markets with the same AWP/FOC laws may not be

[18] The complementary log–log model in Eq. (6) was generated by grouping time in the continuous-time proportional hazard model into intervals (for details see Meyer, 1990). Alternatively, the probability to adopt (conditional on not having already adopted) can be written as $\lambda_{ij}=F(x_{ij}'\beta+\lambda_j)$ where $F(\cdot)$ is the cumulative distribution function of the latent variable. If the latent variable has a standard extreme value distribution, then once again we get the complementary log–log hazard rate model. However, if $F(\cdot)$ is an identity function then we get a linear probability model $\lambda_{ij}=x_{ij}'\beta+\lambda_j+v_{ij}$ where x_2, x_3 and the interactions with x_5 are allowed to be correlated with the error term (as well as x_5 itself).

[19] There are separate AWP and FOC laws for HMOs and other forms of managed care (e.g. PPOs). Further, they specify if the FOC or AWP law applies to hospitals, physicians or pharmacies. In my construction of these instruments, I only consider if the FOC or AWP law applies to HMOs (rather than to PPOs). Thus, 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 in a given year.

Table 4
Estimates of the linear probability model for specifications (4)

	Specification (4)	H-OLS (4A)	H-2SLS (4B)†	H-2SLS (4C)‡
x_2: HMO penetration	−0.0119	−0.0004[a]	−0.0025[b]	−0.0025[c]
	(0.0074)	(0.0001)	(0.0012)	(0.0013)
x_3: # of HMOs	0.0428[a]	0.0011[a]	0.0048[b]	0.0049[b]
	(0.0134)	(0.0003)	(0.0020)	(0.0024)
x_4: # of neighbors	−0.0280[a]	0.0000	0.0001	0.0001
	(0.0072)	(0.0000)	(0.0001)	(0.0001)
x_5: neighbors w./cathlabs last year	0.1323[a]	−0.0002[a]	−0.0005[b]	−0.0005[c]
	(0.0200)	(0.0000)	(0.0002)	(0.0003)
x_2·x_5: (HMO penetration)×(neighbors w./cathlabs)	−0.0000	0.0045[a]	0.0067[a]	0.0068[c]
	(0.0005)	(0.0008)	(0.0026)	(0.0040)
x_3.x_5: (#HMOs)×(neighbors w./cathlabs)	−0.0050[a]	−0.0008[a]	−0.0009[a]	−0.0009
	(0.0009)	(0.0003)	(0.0003)	(0.0013)
	Selected marginals $\left(\frac{\partial \lambda_{ij}}{\partial x_k}\right)$ and standard errors			
x_2: HMO penetration	−.00018[b]	−.00034[a]	−.00214[b]	−.00214[b]
	(.00010)	(.00013)	(.00098)	(.00102)
x_3: # of HMOs	.00042[a]	.00053[c]	.00333[b]	.00334[b]
	(.00018)	(.00031)	(.00158)	(.00186)

Note 1: H-OLS(4B) treats x_2, x_3 and their interactions with x_5 as the endogenous variables but x_5 itself is an exogenous variable. H-OLS(4C) also treats x_5 as an endogenous variable.
Note 2: All specifications include 10 time dummies and 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, teaching school status and, a dummy if the hospital is in a rural area. These regressions exclude observations on new hospitals and hospitals in very dense areas.
Significance of estimates at 1%, 5% and 10% level indicated by a b c respectively. Standard errors are in parenthesis.

Endogenous variables:	†First-stage statistics for H-2SLS (4B)		‡First-stage statistics for H-2SLS (4C)	
	R^2	Weak insts. *F*-test	R^2	Weak insts. *F*-test
x_2: HMO penetration	0.4212	57.78	0.4114	50.59
x_3: # of HMOs	0.6397	114.26	0.6382	118.56
x_2:x_5: (HMO penetration)×(neighbors w./cathlabs)	0.8667	10.40	0.7819	11.90
x_3:x_5: (# of HMOs)×(neighbors w./cathlabs)	0.9243	24.75	0.8778	20.95
x_5: (neighbors w./cathlabs)	–	–	0.9181	18.22
Hausman endogeneity tests	$\chi^2_{(4)}$=4.135, *p*-val=.3880		$\chi^2_{(5)}$=4.135, *p*-val=.5302	
Valid instruments test (Hansen's *J* statistic)	$\chi^2_{(4)}$=1.066, *p*-val=.8997		$\chi^2_{(3)}$=1.050, *p*-val=.7891	

equally attractive to HMOs if one has more large firms than the other. Hence, in some estimates, I also used an interaction of these three instruments as an additional instrument (i.e., $z_4=z_1z_2z_3$).

To construct an independent instrument for x_5 (neighbors with cathlabs in the previous period) I rely on an assumption already used in the main hazard rate model: That a hospital's decision to adopt depends on the neighbors' characteristics (for instance how many of its neighbors have already adopted) but *not* on hospitals that are not its neighbors. Thus, for each hospital, I first identified neighbors' neighbors, and then excluded from this set all hospitals that were also the original hospital's neighbors. Characteristics of these non-overlapping neighbors' neighbors would partially influence the adoption decisions by neighbors' (a relevant instrument), but not the original hospital's decision (a valid instrument) except via their influence on the intermediary neighbors. Thus, I constructed the additional instrument z_5 as the number of neighbors' neighbors who are not the original hospital's neighbors and had also already adopted cathlabs. Finally, note that the main specification includes interaction terms between the HMO variables and the neighbors with cathlabs variable. Thus, in the 'first-stage' I also use the interactions between the instruments for these variables as additional instruments (see Wooldridge, 2002 pp. 231–235). My primary interest here is to check 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 I compute Hausman's statistic ($\chi^2=(\beta_2-\beta_1)^T(V_2-V_1)^{-1}(\beta_2-\beta_1)$) using the GMM estimators for heteroscedastic OLS (H-OLS) and heteroscedastic 2SLS (H-2SLS).[20] Results are summarized in Table 4. The first column redisplays the results from specification (4) of the discrete time hazard model and the second column (labeled H-OLS(4A)) provides H-OLS estimates of the linear probability model (LPM) for specification (4). Note that for H-OLS, x_2, x_3, x_5 and the interaction terms are treated as exogenous. The difference in the magnitude of the coefficients in column 1 and column 2 is 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 the partial of a cloglog function (see Footnote 14). Accounting for the interaction term, the marginals with respect to x_2 and x_3 are comparable in magnitude and are given in the middle section of the table. For instance, the marginal with respect to number of HMOs in specification (4) is .00042 but for the linear model with H-OLS estimates, it is .00053.

The third column (labeled H-2SLS(4B)) provides H-2SLS estimates when x_2, x_3 and their interactions with x_5 are treated as endogenous (but x_5 itself is exogenous). Accounting for the endogeneity of these variables increases the magnitude of the estimated coefficients (and the marginals). However, in a Hausman test between columns (4A) and (4B), the null hypothesis that coefficients in (4A) are consistent (i.e., 'no endogeneity') cannot be rejected ($\chi^2_{(4)}$=4.135, *p*-val=.3880). Additionally, the first-stage statistics indicate that the instruments are relevant and not weak (the joint *F*-stat for the excluded instruments is always greater than 10) and the over identification tests support the earlier claim that the instruments are valid (for instance, the Hansen's *J* statistic is $\chi^2_{(4)}$=1.066, *p*-val=.8997 and hence the null of orthogonality of the excluded instruments with the error term is not rejected). Finally, the last column (labeled H-2SLS(4C)), additionally treats x_5 as an endogenous variable. The results are virtually the same as those in the previous case and all test statistics lead to the same conclusions (also reported at the bottom of the table). These results show that the potential endogeneity of HMO variables (or of the number of neighbors) does not pose any serious problem in the estimation of

[20] 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.

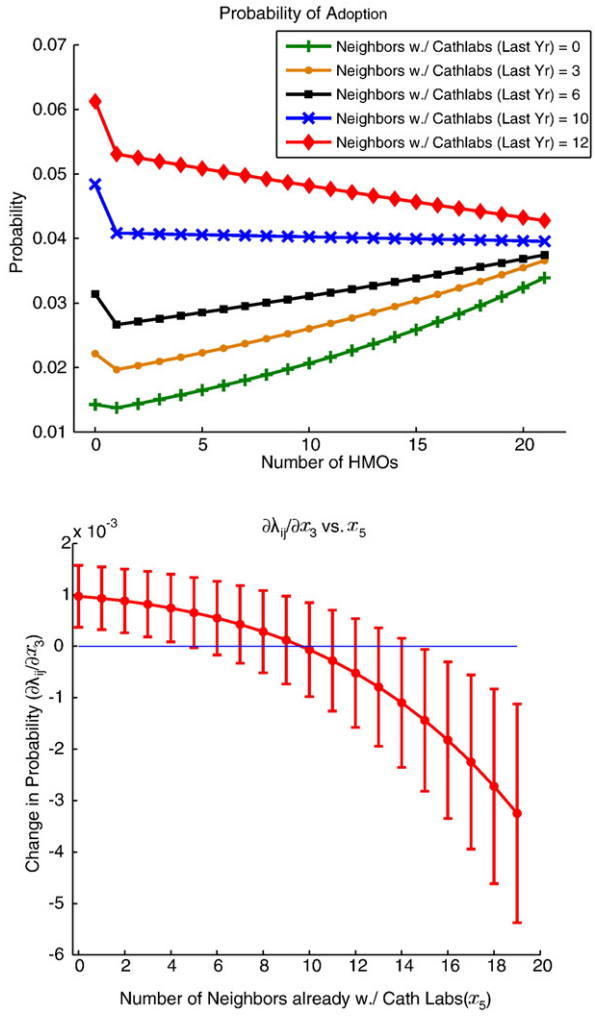

Fig. 1. Probability of adoption.

the linear probability model when endogeneity is ignored. In turn this *suggests* that, even if HMO variables are endogenous, the coefficients and marginals reported in Table 3 may not be necessarily biased.[21]

5. Marginal effects and net adoptions

In all the seven specifications summarized in Table 3, the coefficient on HMO penetration is negative while that on the number of HMOs is positive. However, given the non-linear nature of the hazard (see Eq. (6)) as well as the interaction terms, it is not immediately clear if the hazard (λ_{ij}) increases or decreases with x_2 and x_3 over the range of the data. For instance, since the coefficient on the interaction term ($x_3 \cdot x_5$) between neighbors with catheterization laboratories (in the last period) and the 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.

5.1. λ_{ij} vs. x_3 (given x_5)

To show this, the first panel of Fig. 1 plots the discrete hazard, i.e., the conditional probability of adoption given that the hospital has not already adopted (see Eq. (6)) 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*. Two things are worth noting from these graphs. First, at all levels of x_5 when the number of HMOs increases from zero to one, there is a dip in the curves showing that the probability of adoption decreases. This is a pure penetration effect since there is only one HMO in the market.[22] Second, when the number of neighbors that had already adopted is low (x_5=0, 3 or 6), the probability curve (as a function of the number of HMOs) slopes upwards and the slope becomes zero (for x_5=10) or negative (for x_5=12) for large values of x_5. The graph shows that as the number of HMOs increases, 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 the first adoption (neighbors with cathlabs in last period=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 the 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. Whether these slopes (i.e. the marginals) are *statistically* positive, and later negative, is discussed next.

5.2. $\partial\lambda_{ij}/\partial x_3$ vs. x_5

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 3 and varied from .00041 to .00048 across specifications 1 through 7). The second panel of Fig. 1 plots the marginal probability with respect to the 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 intervals (as before, s.e. computed via the delta method). The figure shows that $\frac{\partial\lambda_{ij}}{\partial x_3}$ is positive until about the 10th 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 15th 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 $\frac{\partial\lambda_{ij}}{\partial x_3}$ is less than zero in markets where technology is already well diffused.[23]

[21] The results were also robust to several alternative versions of the excluded instruments. For instance, in (4B) since it is assumed that x_5 is exogenous, it is possible to construct alternative instruments as the interaction of x_5 with the instruments for the HMO variables. The results from these alternative instruments are available from the author upon request.

[22] However, this result is not statistically robust. The computed (cluster-robust) standard errors were large since the simulations at this point are mostly out of sample. For instance, there are no observed markets where 12 neighboring hospitals have already adopted cathlabs and there are no HMOs in the market.

[23] 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, the marginal probability of adoption with respect to the number of HMOs is positive.

Table 5
Predicted adoptions

Scenario	Adoptions (±95% CI)
Observed adoptions	560
Model predicted adoptions	555 (±45)
Penetration held at 1% in each market, # of HMOs grows	617 (±81)
Penetration held at 1985 mean value, # of HMOs grows	577 (±51)
Penetration grows, # of HMOs held at 1 per market	491 (±62)
Both penetration and # of HMOs held at 1985 mean values	556 (±49)

Note: $N=31,306$ and corresponds to hospital-years where $x_5 \leq 10$. Adoptions are computed as $A = N \times \bar{\hat{g}}_i = \sum_i \hat{g}_i$ where $\hat{g}_i$ is the predicted probability for the ith observation.

5.3. Net adoptions

Does an increase in managed care activity slow the diffusion of technology? While there is no simple answer 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. 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 average predicted probability of adoption was 0.0177 and the risk set was 31,306 (i.e., hospital-years between 1986 and 1995 comprising of hospitals that had not adopted by 1985). Multiplying 31,306 by 0.0177 gives 555 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, then assuming a binomial distribution for number of adoptions may not provide a bad approximation.[24] Thus, in a couple of simple exercises, I recomputed the probability of adoption 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. Results are summarized in Table 5. Setting HMO penetration equal to 1% in each market changes the predicted number of adoptions to 617 and setting it equal to the average value in 1985 (7.82%, see Table 2) changes the predicted adoptions to 577. Both suggest that an increase in HMO penetration resulted in fewer adoptions (by 62 and 22 respectively) than had there been no increase in HMO penetration. Further, similar calculations also show that had there been exactly one HMO in each market and everything else changed as is observed in the data (including HMO penetration which on average increased from 7.83% to 20.37% over 1985–1995) then the number of adoptions would have been only 491 (or if penetration is kept at the 1985 level then there would have been 505±60 adoptions). Thus, the presence of additional HMOs can be associated with 64 additional adoptions. Finally, the net impact of HMOs, due to an increase in both the number of HMOs and HMO penetration can be judged by holding these variables to their 1985 values. Doing so results in 556 adoptions. Note that this value is not very far from the true predicted value of 555, suggesting that the *net impact of HMO activity on the adoption of cathlabs has been very small.*

6. Summary

Managed care organizations change the incentives faced by health care providers which in turn can have significant implications for the diffusion of technology. This paper finds that an increase in HMO penetration is associated with a slower diffusion of cardiac catheterization laboratories. However, an increase in HMO competition (whether measured as the number of HMOs, HMOs per capita or by the Herfindahl index) has a countervailing effect in that it increases the probability of adoption.

The results can be understood in the context of bargaining between HMOs and hospitals. A monopoly HMO can obtain large discounts from hospitals which in turn reduces the profitability of the hospitals and slows diffusion of expensive technologies. As the number of HMOs increases, their bargaining position weakens, resulting in lower discounts by hospitals. However, this latter effect is non-linear and arises due to an inherent trade-off in the expected volume of a hospital when additional hospitals join the HMO's network: If the network is small, each hospital in the network gets a larger share of the HMO enrollees who use the network hospitals but if the network is large, while each hospital gets a smaller share of the enrollees, more enrollees receive services from network hospitals.

Simulations for cathlabs show that when there are relatively few neighbors that have adopted the technology, an increase in the number of HMOs increases the probability of adoption but when many have already adopted the technology, the effect of the number of HMOs is the opposite. However, the effect of penetration is always to reduce the adoption probability. Thus, when technology is still diffusing (i.e. is relatively rare) competition and penetration work in opposite directions and the net effect could be positive or negative. In fact, when penetration and number of HMOs at held at their 1985 values, the predicted number of adoptions is the same as the actual observed number of adoptions. While these are only simulations, they do suggest why the prior literature, which has ignored the competition effect, has sometimes reported mixed results on HMO penetration. The results are robust for the case of cardiac catheterization laboratories, however, it would be useful to check them for other important hospital technologies — choosing some that had not yet well diffused over the period when HMO penetration and competition were increasing and others that were already (relatively) well diffused.

Appendix A

This appendix derives the optimal bid given in Eq. (3) on page 4.

Basic setup: There are K non-network hospitals. For all hospitals, the unit price of service is 1, unit cost is $c_i \sim U[0, 1]$ and is iid. The distribution is known by all but the realization of c_i is known only to the hospital. The jth HMO is soliciting discount bids from these K hospitals. The bidder with the largest discount d is added to the jth HMO's network such that the size of the network increases from G_j to G_j+1. Also, γ_j is the parameter that measures the control of the HMO to restrict its enrollees to use in-network hospitals. Thus, $\gamma_j=1$ means that with probability 1, an enrollee will use one of the G_j+1 in-network hospitals and if $\gamma_j=(G_j+1)/(G_j+K)$ then the HMO has no control over its enrollees and an enrollee will visit any of the G_j+K hospitals with equal probability. Thus, the ith hospital's problem is to find d_i^* such that the expected profit is maximized, i.e.,

$$\max_{d_i}\left((1-d_i-c_i)\frac{\gamma_j S_j}{G_j+1}-\alpha\right)\Pr(d_i>d^*(c_k)\forall k\neq i) + \left((1-c_i)\frac{\left(1-\gamma_j\right)S_j}{K-1}-\alpha\right)(1-\Pr(\cdot)). \quad (A-1)$$

Solution: Assume that d^*, if it exists, is monotonic and decreasing in c_i (decreasing because hospitals are bidding a discount below the price of 1) and then verify that the solution is indeed monotonically decreasing in c_i. Envision that the way the bidding will take place is that the bidder will pretend that his unit cost is some value r and will bid according to the discount bid function with the value of r. Then the

[24] This assumption is technically not correct. A random variable Y where Y is the number of successes observed during n trials 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.

problem reduces to maximizing the objective function given above over r. Thus, hospital i will win the bid with probability

$$\Pr(d^*(r)>d^*(c_k)\forall k\neq i)\rightarrow\Pr(r<c_k\forall k\neq i). \quad (A-2)$$

For any one given c_k, let $Pr(r<c_k)=1-Pr(c_k<r)=1-F(r)$. Then, due to the independence assumption of c_k, $Pr(r<c_k\ \forall k\neq i)=(1-F(r))^{(K-1)}$. Rewriting the last probability as $\rho(r)$, the maximization problem is just

$$\max_r (1-d_i-c_i)\frac{\gamma_j S_j}{G_j+1}\rho(r)+(1-c_i)\frac{\left(1-\gamma_j\right)S_j}{K-1}(1-\rho(r))-\alpha. \quad (A-3)$$

From the FOCs we get

$$\begin{aligned}
&\partial(\text{Obj Fn})/\partial r=0\\
&\Rightarrow\frac{(1-d^*(r)-c_i)\gamma_j S_j}{G_j+1}\rho'(r)-d'^*(r)\frac{\gamma_j S_j}{(G_j+1)}\rho(r)-\rho'(r)\frac{(1-c_i)\left(1-\gamma_j\right)S_j}{(K-1)}=0\\
&\Rightarrow\frac{\gamma_j S_j}{G_j+1}\{d^*(r)\rho'(r)-d'^*(r)\rho(r)\}=(1-c_i)\rho'(r)\frac{\gamma_j S_j}{G_j+1}-(1-c_i)\rho'(r)\frac{\left(1-\gamma_j\right)S_j}{(K-1)}\\
&\Rightarrow\frac{\gamma_j}{(G_j+1)}\frac{\partial}{\partial r}\{d^*(r)\rho(r)\}=(1-c_i)\rho'(r)\left[\frac{\gamma_j}{G_j+1}-\frac{1-\gamma_j}{K-1}\right]
\end{aligned} \quad (A-4)$$

In order to solve for d^*, we use the fact that in equilibrium we must have $r=c_i$, integrate from c_i to 1 and use the boundary condition that $d^*(1)=0$. Thus,

$$\frac{\gamma_j}{(G_j+1)}\int_{c_i}^{1}\frac{\partial}{\partial t}\{d^*(t)\rho(t)\}dt=\frac{-\gamma_j}{(G+1)}\rho(c_i)\rho^*(c_i) \quad (A-5)$$

which gives

$$d^*(c_i)=-\frac{(G_j+1)}{\gamma_j\rho(c_i)}\left\{\int_{c_i}^{1}(1-t)\rho'(c_i)\left[\frac{\gamma_j}{G_j+1}-\frac{1-\gamma_j}{K-1}\right]\right\}dt. \quad (A-6)$$

In order to integrate, note that $\rho'(r)=(K-1)(1-F(r))^{(K-2)}(-f(r))$ and $c_i\sim U[0,1]$ (and iid), so $F(r)=r$ and $f(r)=1$. Thus,

$$\begin{aligned}
&\rho(c_i)=(1-c_i)^{(K-1)}\\
&\text{and}\quad \rho'(c_i)=(K-1)(1-c_i)^{(k-2)}(-1)
\end{aligned} \quad (A-7)$$

and substituting these back in the expression for $d^*(c_i)$ above, we get

$$\begin{aligned}
d^*(c_i)&=-\frac{(G_j+1)(K-1)}{\gamma_j\rho(c_i)}\left[\frac{\gamma_j}{G_j+1}-\frac{1-\gamma_j}{K-1}\right]\left\{\int_{c_i}^{1}(1-t)(1-t)^{(K-2)}(-1)dt\right\}\\
&=-\frac{(G_j+1)(K-1)}{\gamma_j(1-c_i)^{(K-1)}}\left[\frac{\gamma_j}{G_j+1}-\frac{1-\gamma_j}{K-1}\right]\left\{\int_{c_i}^{1}(1-t)^{(K-1)}(-1)dt\right\}
\end{aligned} \quad (A-8)$$

which simplifies to

$$d^*(c_i)=\frac{(1-c_i)}{K}\left((K-1)-\frac{\left(1-\gamma_j\right)(G_j+1)}{\gamma_j}\right). \quad (A-9)$$

Note that Sorensen's (2003) result is reproduced for $G_j=0$, $K=2$.

Appendix B

This table provides a detailed version of Table 3 from the paper and includes MLE estimates for variables that were not reported there.

Clustered s.e. in parenthesis. Superscripts a, b imply significance at 1% and 5% respectively.

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
x_1: intercept	−5.7806[a]	−5.8980[a]	−5.9462[a]	−5.9529[a]	−6.0028[a]	−6.1562[a]	−63.4287[a]
	(.2611)	(.2789)	(.2827)	(.2855)	(.2895)	(.3047)	(11.0187)
x_2: HMO penetration	−.0139[b]	−.0145[b]	−.0145[b]	−.0119	−.0119	−.0104	−.0039
	(.0071)	(.0074)	(.0074)	(.0074)	(.0074)	(.0074)	(.0075)
x_3: # of HMOs	.0456[a]	.0466[a]	.0465[a]	.0428[a]	.0427[a]	.0406[a]	.0377[a]
	(.0126)	(.0130)	(.0130)	(.0134)	(.0134)	(.0132)	(.0137)
x_4: # of neighbors	−.0316[a]	−.0334[a]	−.0335[a]	−.0280[a]	−.0282[a]	−.0287[a]	−.0296[a]
	(.0065)	(.0067)	(.0067)	(.0072)	(.0072)	(.0072)	(.0072)
x_5: neighbors w./cathlabs last year	.1126[a]	.1200[a]	.1202[a]	.1323[a]	.1324[a]	.1301[a]	.1221[a]
	(.0194)	(.0201)	(.0201)	(.0200)	(.0200)	(.0201)	(.0202)
x_2·x_5: (HMO penetration)×(neighbors w./cathlabs)	.0006	.0007	.0007	−.0000	−.0000	.0001	−.0002
	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)	(.0005)
x_3·x_5: (# HMOs)×(neighbors w./cathlabs)	−.0047[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0050[a]	−.0040[a]
	(.0008)	(.0008)	(.0008)	(.0009)	(.0009)	(.0009)	(.0009)
x_8: CON law dummy. 1 if law in effect in state-year	–	–	–	–	–	.2322[b]	.1010
						(.1083)	(.1103)
x_9: year 10% of farms adopted tractors	–	–	–	–	–	–	.0296[a]
							(.0057)
x_{10}: rural area dummy. 1 if rural area	−3.1564[a]	−3.1238[a]	–	−3.1053[a]	–	–	–
	(.7095)	(.7096)		(.7098)			
x_{11}: per capita income (1982–84 constant 1000's $)	.0661[a]	.0686[a]	.0691[a]	.0717[a]	.0723[a]	.0690[a]	.0864[a]
	(.0133)	(.0137)	(.0138)	(.0146)	(.0146)	(.0150)	(.0149)
x_{12}: per capita AFDC $ (1982–84 constant 1000's $)	−.0029[a]	−.0029[a]	−.0029[a]	−.0023[b]	−.0023[b]	−.0024[b]	−.0015
	(.0010)	(.0010)	(.0010)	(.0011)	(.0011)	(.0011)	(.0011)
x_{13}: population over 65 (in 100,000s)	.4441[a]	.4515[a]	.4510[a]	.4246[a]	.4241[a]	.3537[b]	.3410[b]
	(.1436)	(.1482)	(.1481)	(.1504)	(.1503)	(.1538)	(.1485)
x_{14}: square of population over 65 (in 100,000s)	.0131	.0124	.0127	.0113	.0116	.0074	−.0035
	(.0212)	(.0219)	(.0219)	(.0229)	(.0230)	(.0231)	(.0233)
x_{15}: total population (in 100,000s)	−.0042	−.0049	−.0051	−.0122	−.0123	.0021	.0020
	(.0169)	(.0174)	(.0174)	(.0175)	(.0176)	(.0186)	(.0183)
x_{16}: 1/0 dummy — 1 for-profit	−.0092	.0202	.0209	.0318	.0326	.0500	−.1038
	(.1230)	(.1254)	(.1254)	(.1248)	(.1248)	(.1248)	(.1243)

(continued on next page)

Appendix B *(continued)*

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
x_{17}: 1/0 dummy — 1 if medical school affiliated	.9668[a]	.9697[a]	.9698[a]	.9483[a]	.9484[a]	.9303[a]	.8940[a]
	(.1126)	(.1137)	(.1137)	(.1142)	(.1142)	(.1144)	(.1152)
d_{86}: year 1986 dummy	1.0191[a]	1.0938[a]	1.1394[a]	1.0758[a]	1.1231[a]	1.1182[a]	1.1744[a]
	(.2432)	(.2561)	(.2603)	(.2588)	(.2633)	(.2640)	(.2645)
d_{87}: year 1987	.7042[a]	.7911[a]	.8364[a]	.7397[a]	.7866[a]	.7804[a]	.8217[a]
dummy	(.2514)	(.2637)	(.2678)	(.2703)	(.2746)	(.2749)	(.2762)
d_{88}: year 1988 dummy	.8468[a]	.9428[a]	.9880[a]	.9369[a]	.9835[a]	1.0048[a]	1.0109[a]
	(.2425)	(.2551)	(.2593)	(.2577)	(.2622)	(.2638)	(.2638)
d_{89}: year 1989 dummy	.6786[a]	.7250[a]	.7697[a]	.7211[a]	.7674[a]	.7873[a]	.7918[a]
	(.2479)	(.2604)	(.2644)	(.2624)	(.2668)	(.2683)	(.2682)
d_{90}: year 1990 dummy	.9969[a]	1.0229[a]	1.0675[a]	1.0272[a]	1.0734[a]	1.0896[a]	1.0937[a]
	(.2414)	(.2567)	(.2608)	(.2597)	(.2641)	(.2656)	(.2664)
d_{91}: year 1991 dummy	1.1119[a]	1.1996[a]	1.2444[a]	1.1986[a]	1.2450[a]	1.2546[a]	1.2602[a]
	(.2468)	(.2606)	(.2646)	(.2615)	(.2658)	(.2668)	(.2667)
d_{92}: year 1992 dummy	.9475[a]	1.0577[a]	1.1019[a]	1.0403[a]	1.0861[a]	1.0983[a]	1.0909[a]
	(.2710)	(.2815)	(.2852)	(.2815)	(.2855)	(.2868)	(.2878)
d_{93}: year 1993 dummy	.9620[a]	.9893[a]	1.0334[a]	.9633[a]	1.0090[a]	1.0147[a]	1.0261[a]
	(.2370)	(.2529)	(.2569)	(.2581)	(.2624)	(.2632)	(.2626)
d_{94}: year 1994 dummy	.7395[a]	.7331[a]	.7575[a]	.7553[a]	.7814[a]	.7852[a]	.8095[a]
	(.2444)	(.2618)	(.2664)	(.2652)	(.2701)	(.2713)	(.2712)
d_{95}: year 1995 dummy	–	–	–	–	–	–	–
Observations	35,834	35,103	32,033	34,230	31,160	31,160	31,160

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