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THE DETERMINANTS OF TECHNOLOGICAL CHANGE IN HEART ATTACK TREATMENT

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ABSTRACT

This paper examines the sources of expenditure growth in heart attack treatment. We first show that essentially all of cost growth is a result of the diffusion of particular intensive technologies; the prices paid for a given level of technology have been constant or falling over time. We then examine the reasons for this technology diffusion. We distinguish six factors that may influence technology diffusion: organizational factors within hospitals; the insurance environment in which technology is reimbursed; public policy regulating new technology; malpractice concerns; competitive or cooperative interactions among providers; and demographic composition. We conclude that insurance variables, technology regulation, and provider interactions have the largest quantitative effect on technological diffusion. These factors affect both technology acquisition and the frequency of technology use.

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Persistent growth in health expenditures over the past several decades has moved the cost of health care to the top of the policy agenda. In the United States and most of Europe, spending on health care has become a political as well as economic issue, and proposals to limit spending are commonplace.

Despite this widespread concern, very little is known about the fundamentals of health expenditures. At an accounting level, Aaron (1991) and Newhouse (1992) both show that "static" supply and demand factors such as increased moral hazard or administrative expense can explain less than half of the growth of medical spending; each attributes the residual to technological change. Fuchs (1996) shows that this view has become a consensus among health economists. But despite this consensus, direct evidence on the role of technological change in cost growth is lacking, and there is little analysis of the reasons for this rapid technological change.

In this paper, we analyze the importance of technological change in explaining medical care cost increases and determine the factors explaining technological diffusion. Previous work has typically considered the importance of technological change by looking at cost growth in aggregate. Since medical conditions and technologies vary so much from disease to disease, however, the aggregate approach cannot yield firm estimates of the importance of technological change for medical care costs. We thus focus on technology for a particular medical condition: acute myocardial infarction (AMI, or heart attack). Heart disease, of which heart attacks are a serious complication, is the single leading cause of death in the United States and accounts for around one-seventh of all medical expenditures. In addition, technology used in the treatment of heart disease has changed tremendously in the past decade. Thus, analyzing technology involved in treating heart attacks sheds light on the determinants of technological change in a case where it really matters.

We begin by decomposing expenditure growth for heart attack care into the share of patients receiving intensive procedures and the price of these procedures. We show that essentially all of the growth in costs results from the diffusion of intensive technologies -- the development of entirely new technologies and the diffusion of existing technologies to new patients. The price of a given treatment has been constant or falling over time. Thus, measuring spending directly at the micro level suggests that technological change accounts for an even larger share of cost increases than the aggregate residual analysis suggests.

We then examine why costly technologies for heart attack care have diffused so rapidly. We distinguish six theories of the determinants of technology diffusion: organizational factors within hospitals; the insurance environment governing the technologies' use; public policy regulating technologies; malpractice concerns on the part of providers; competitive or cooperative interactions among providers; and demographic change. We find that the insurance environment, technology regulation, and provider interactions are most important in explaining technology diffusion. Together, these factors explain a significant part of technology diffusion and suggest that some policies can have long-run effects on the rate of technological change in medicine.

The paper is organized as follows. Sections I and II describe treatment of heart attacks and examine the sources of cost increases in heart attack treatments. Section III then discusses the factors that may influence the diffusion of technology. Sections IV through VI examine the determinants of technological change. The last section concludes.

I. The Cost of Heart Attack Treatment

We focus on technological change in heart attack treatment. Heart disease, of which heart attacks are a leading example, accounts for one-seventh of medical spending and is the leading cause of death in the United States. In addition, people with a heart attack will necessarily be admitted to a hospital, so that hospital records can be used to trace incidence and treatments.

To measure the cost of heart attack treatment, we developed a sample of Medicare hospital claims for essentially all elderly patients hospitalized with AMI between 1984 and 1991.[1] Our focus on the elderly is largely for data reasons: long-term, longitudinal data on the non-elderly U.S. population are not available. Most AMIs occur in the elderly, however, and the same technologies used in treating AMI in the elderly are used in treating nonelderly patients, so our restriction to the elderly should not be a major concern.

Heart attack treatment may involve followup care in and out of hospitals for a period of several months. We include all admissions within a 90 day period after the initial attack in a heart attack episode, and use this episode as the basis for our subsequent analysis. There are roughly 230,000 new heart attacks episodes in the elderly per year.

Table 1 shows summary statistics on Medicare reimbursement for heart attack episodes between 1984 and 1991. As the first row shows, average reimbursement per heart attack patient (in 1991 dollars) rose from $11,175 in 1984 to $14,772 in 1991, for a 4 percent annual increase.[2] In total, inpatient expenditures for a heart attack among those 65 and over rose from $2.6 billion in 1984 to $3.4 billion in 1991. Clearly, spending for heart attack treatment is a major issue for the medical sector.

To understand the source of this cost increase, it is necessary first to describe the treatment of heart attacks in more detail. One set of technologies for treating heart attacks involves "medical

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[1]The process for developing the claims data are described elsewhere (McClellan and Newhouse, 1994; McClellan, 1995b).

[2]This increase roughly equals the growth in aggregate medical expenditures (4.7 percent in real per capita terms) over the same period.

management": in the acute period, drug therapies, monitoring technologies, and intensive-care interventions if needed for heart failure or irregular heart rhythms; later, drug therapy and counseling to promote a healthy lifestyle and reduce the risk of future heart attacks. This type of care involves many important technologies -- for example, thrombolytic (clot-busting) drugs were developed in the 1970s and used on a wide-scale basis in the 1980s -- but it does not involve invasive procedures to restore blood flow to the heart.

These invasive cardiac treatments begin with *cardiac catheterization* -- a radiologic study of blood flow to the heart muscle. Catheterization was developed in the late 1960s and became more widely used in the treatment of patients with heart disease over the next decade. If the catheterization detects "significant" blockage, a range of revascularization procedures may be performed with the goal of eliminating the blockage. Two major types of revascularization procedures have become widely used: *bypass surgery*, a major open-heart operation that involves bypassing blocked blood vessels, and *angioplasty*, a percutaneous (less invasive) procedure that seeks to restore blood flow via inflating a balloon amid the blockage. Bypass surgery was also developed in the late 1960s. Angioplasty is a more recent technology. It was first applied clinically in the late 1970s but did not become a Medicare-covered service until November 1982. Since angioplasty was the most recent technology, examining the diffusion of this technology provides the best evidence on how a medical technology progresses from being rarely to widely applied. We thus focus on this technology in particular in our empirical work.

All of these procedures have undergone considerable refinement over time, as cardiologists and cardiac surgeons have identified "process" improvements and developed experience with patients who benefit from them.

All of these procedures also involve substantial fixed and variable costs. Performing catheterization requires specialized equipment (radiologic scanners, monitoring devices, and dedicated catheterization devices) as well as specialized cardiac nurses and technicians. Angioplasty requires a catheterization lab plus additional investments in specialized staff and devices. Bypass surgery is the most costly technology, requiring equipment such as heart-lung bypass machines and nurses with training for cardiac operations and cardiac intensive care.

This set of treatment paths provides a natural mechanism for decomposing spending growth. The middle rows of the Table show what has happened to prices paid for intensive procedures, and the share of patients receiving these procedures over time.[3] Real spending for patients with a catheterization only or angioplasty fell,[4] while spending for patients who were managed medically or received bypass surgery rose slightly. The penultimate row of the Table shows that a Paasche "price index" for heart attacks treatments actually fell by 0.2 percent annually.[5]

In contrast to essentially flat prices, there has been a dramatic increase in the use of intensive cardiac procedures over time. Figure 1 and the left columns of Table 1 show the share of heart attack patients receiving intensive treatments. Between 1984 and 1991, the rate of cardiac catheterization quadrupled, from 11 percent to 41 percent. The share receiving bypass surgery nearly tripled (from 5 percent to 13 percent) and the share receiving angioplasty rose 10-fold (from 1

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[3]Some patients receive both angioplasty and bypass surgery, for example because the angioplasty failed and bypass surgery was necessary. We group these patients in the bypass surgery group.

[4]The reimbursement rate for angioplasty was reduced substantially in 1986 as officials realized it was much less expensive than the DRG it was assigned to and thus reassigned it to a lower-weighted DRG. Reimbursement for catheterization changed as more catheterizations were done in the initial hospital stay rather than in multiple stays. See Cutler and McClellan (1996) for more discussion.

[5]Cutler, McClellan, Newhouse, and Remler (1996) discuss the formulation of a price index for heart attack care in more detail.

percent to 12 percent). Thus, in only an 8-year period, the treatment of heart attacks changed fundamentally. The diffusion of these technologies almost entirely explains expenditure growth. As the last row of the Table shows, the change in procedure use holding prices constant accounts for a 3 percent annual increase in real spending.[6]

Thus, explicit measurement of changes in technology use demonstrates that technology diffusion explains an even larger share of expenditure growth than was suggested by previous studies based on residual analysis. In the remainder of the paper, we examine the determinants of technology diffusion. We begin with a simple characterization of technology change.

II. Characterizing Technological Diffusion

Figure 1 demonstrates a fundamental point about technology diffusion: technological diffusion involves both the application of new technologies *and* the expanded use of existing technologies. Two of the technologies with rapid procedure growth (catheterization and bypass surgery) were well developed by 1984, while one technology (angioplasty) was essentially new. This type of situation is consistent with Rosenberg's (1994) analysis of the importance of technology diffusion in many industries. It highlights that economic explanations for diffusion must focus on both the intensive margin of procedure use as well as the extensive margin of technology acquisition.

Increases in procedure use can occur for one of three reasons: new hospitals acquire technologies; hospitals with the technology expand their use of it; or hospitals without the technology transfer more patients to hospitals with the technology, where they receive it. We sort patients on the basis of their hospital of initial admission, since heart attack patients tend to be taken

[6]The remaining source of cost growth is the covariance between price and quantity changes.

to a nearby hospital first, and the initial hospital choice has a substantial impact on the patient's entire course of treatment.[7] The probability that a patient receives a particular procedure can be decomposed into:

$$Pr[Use] = Pr[Own]\cdot(Use|Own) + (1-Pr[Own])\cdot(Use|Not\ Own) \quad (1)$$

where *Pr[Own]* is the probability that the hospital to which the patient was initially admitted had acquired the procedure, *(Use|Own)* is the probability that a patient whose initial admission was at a hospital that owned the procedure receives the procedure within 90 days and *(Use|Not Own)* is the probability that a patient initially admitted to a hospital without the procedure is transferred or readmitted to another hospital within 90 days and undergoes the procedure.

Table 2 shows evidence on the importance of these three terms to total intensity growth. The first rows of Table 2 report the share of hospitals with each technology in 1984 and 1991. We count a hospital as having adopted the procedure the first year it reported performing it 3 or more times.[8] The availability of these technologies increased substantially over the period, roughly doubling in each case.

Patients initially admitted to hospitals with intensive technologies are substantially more likely to receive these technologies than patients admitted to hospitals without these intensive technologies. Figure 2 shows this in the case of angioplasty. In 1991, patients initially admitted to

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[7]See McClellan (1993) and McClellan and Newhouse (1996) for a more detailed discussion of the impact of technology availability and adoption on hospital practices.

[8]Conditioning on 3 uses is done to avoid data errors from improper coding on claims forms. To count procedures, we look at the discharge records for both AMI patients and patients with ischemic heart disease (IHD, a milder form of heart disease). Including this latter group allows us to be more precise in technology ownership for hospitals with few AMI patients. There are about 350,000 new IHD cases annually.

hospitals with angioplasty (the average of the top two lines) received the procedure nearly twice as frequently as patients admitted to hospitals without the capacity to perform angioplasty. This differential implies that the spread of technological ownership is an important component of technology diffusion. Indeed, as the second block of Table 2 shows, the increase in the number of hospitals with each procedure -- holding utilization rates constant at their 1991 levels -- accounts for between 10 and 20 percent of total increase in procedure use.[9]

Figure 2 also shows substantial increases in procedure use in hospitals both with and without the technology throughout the 1984-1991 period. The rate of angioplasty use rose from 3 percent to 21 percent in hospitals with the technology each year, and from 0.5 percent to 9 percent in hospitals without the technology in any year. As the last two rows of Table 2 show, each of these factors accounts for 30 to 60 percent of total procedure use. Thus, it is important to examine both the ownership of technologies and their ultimate utilization.

To develop some sense for technology ownership patterns, Table 3 shows statistics for the 5,253 hospitals with at least one admission for AMI in 1991. Roughly half of hospitals have fewer than 100 beds. But these hospitals receive only about 10 percent of the AMI patients, and fewer than 1 percent of them have invested in angioplasty or bypass surgery. As the size of the hospital increases, the number of patients and intensity of technology increase as well. Eight percent of hospitals with 100-199 beds had angioplasty capability, and nearly 90 percent of hospitals with 600 or more beds had the technology. Since AMI admissions and technology ownership are so scarce at small hospitals, we focus our empirical analysis exclusively on hospitals with 100 or more beds.

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[9] This estimate is likely to be a lower bound on the importance of acquisition to technology diffusion since the ability of hospitals without the procedure to transfer patients to where they can receive the procedure depends on the share of other hospitals with the procedure.

There is also a dramatic regional pattern to technology diffusion. Figure 3 shows the geographic spread of angioplasty in 1984, when it was used in the treatment of only one percent of elderly AMI patients. Each marker in the Figure is a zip code with a hospital that had acquired the procedure. Even very early on, the diffusion of angioplasty was geographically widespread. This is important because it suggests that we can use the regional variation in the structure of the health system to learn about the sources of technology diffusion.

Even with the widespread spatial diffusion, there are clear regional differences in technology acquisition. Angioplasty diffused very rapidly in the West, and much less rapidly in the Mid-Atlantic and Southeast. This regional pattern is not unique to angioplasty. Numerous studies have documented substantial regional differences in medical treatments which are very stable over time (Phelps, 1992). To control for these underlying regional and city size differences, we include 9 region dummy variables and 7 dummy variables for city size in all of our econometric models.

III. Explanations for Technological Change

A great deal of theoretical research has speculated on the causes of technological diffusion in medicine.[10] We group the hypotheses into 6 categories.

Organizational Factors. A first set of issues is the organization of the hospital. Some hospitals, because of their size or commitment to innovative care, will be more likely to acquire technologies than other hospitals. As shown above, there are dramatic variations in patient distribution and ownership rates by size of hospital. We thus limit ourselves to hospitals having 100 or more beds,

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[10]See Griliches (1988) for a review of the economics of technical change more generally.

and control for the number of beds within this set, as shown in Table 3. We also include dummy variables for government hospitals, for-profit hospitals, and teaching hospitals. Several studies have suggested that not-for-profit hospitals and teaching hospitals may use technology more intensively than for-profit hospitals, perhaps because not-for-profit hospitals value patient welfare more than for-profit hospitals or because these hospitals feel it is their social obligation to provide high quality care to everyone (Weisbrod, 1988; Hoerger, 1991). Government hospitals may also provide different types of care than private hospitals, because their patient mix is different or revenues are scarcer. The first block of Table 4 shows that these hospitals account for about 15 percent of the sample in each case.

Insurance generosity. Many analysts have hypothesized that the insurance environment can influence technological change. There are a number of potential links between insurance and technological change. One channel is the "profitability" effect -- as insurance becomes less generous, new technologies become less profitable and thus diffuse less widely. Less generous insurance or increased monitoring of physicians may also change practice patterns in a way that encourages less use of new technologies (Feldstein, 1971; Pauly, 1986; Weisbrod, 1991). Countering this, however, is the "income" effect -- if technology is profitable at the margin, cuts in inframarginal reimbursement may induce more utilization so that total profits remain roughly the same. For example, Medicare pays near average cost for intensive surgical procedures even though marginal cost is likely to be substantially lower than average cost. As a result, intensive cardiac procedures are generally considered to be profitable for the marginal treatment. Thus, if reimbursement is cut for non-Medicare patients or the needs of the uninsured rise, hospitals may increase their utilization of intensive cardiac procedures to offset some of the income loss. There is some evidence for this model when physician reimbursement rates are reduced (Christenson, 1992).

We use several measures of the generosity of insurance in our empirical work. The first two variables reflect the nature of overall insurance coverage: the share of the population that is uninsured, and the share of the population that is in Health Maintenance Organizations (HMOs).[11] The uninsurance rate is formed from the March 1989 and 1990 CPS surveys; we match MSAs where possible, and the rest of the state in other cases. HMO enrollment is from Interstudy. The data are at the state level; no published data give HMO enrollment at a more disaggregated level. Since HMO enrollment increases over time, we treat this enrollment as time-varying in our econometric model. As Table 4 shows, the average hospital was in an area where 14 percent of people were uninsured and 13 percent were in HMOs in 1991.

We also include an indicator for whether the state regulated hospital payments by all or most payers. These regulations typically placed limits on per-diem or per-case reimbursement to hospitals. Some previous research has found these regulations to be moderately effective in limiting cost growth, but the conclusions are controversial (Dranove and Cone, 1985). Seven states had such regulation for at least some of the period: Connecticut, Maryland, Massachusetts, New Jersey, New York, Rhode Island, and Washington. Two of the states (Massachusetts and Washington) ended rate regulation after 1988; we treat these states as having the regulation during the period it was in force. These regulations as well may increase or decrease technology diffusion.

We also tried to estimate the effects of hospital payment generosity within the Medicare system on technology adoption decisions. This requires a measure of the generosity of reimbursement that varies independently across hospitals. Under the Prospective Payment System

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[11] HMOs are the most restrictive form of managed care; they often have their own clinics or hospitals that members are required to visit to receive care.

(PPS), hospital payments for Medicare depend on the "weight" of the diagnosis-related group for an admission, and the weights do not vary across hospitals. However, adjustments to the basic DRG payment do vary as a function of hospital characteristics such as urbanicity and teaching status. The problem with using these variations as a measurement of payment generosity is that the hospital characteristics that lead to the payment variations may have a direct association with likelihood of technology adoption.[12] This source of variation thus does not seem appropriate for our analysis.

An alternative measure of PPS generosity is the "bite" of the system -- the extent to which hospital payments changed with PPS adoption. The change in overall Medicare payment associated with PPS depends on the use of intensive technologies such as the ones described above, however (McClellan, 1996). We experimented with a broad range of techniques to construct an exogenous measure of reimbursement generosity. Our resulting estimates were sensitive to the correction method, however, so we do not have great confidence in these results. We thus do not report results using a "bite" variable. We suspect that it will be necessary to examine more technologies with different reimbursement profiles in order to identify effects of Medicare reimbursement on technology acquisition.

Technology regulation. States and the Federal government have used a variety of regulatory methods to limit use of technology. These methods range from regulations requiring advance approval of technology acquisition ("Certification of Need" requirements) to detailed reviews, prospectively or retrospectively, of the use of technology in particular cases (such as peer review organization activities in the Medicare program). To capture this, we include a dummy variable for

[12]These "direct" hospital effects are largely included in our models. However, if the direct effects are nonlinear, then this method will not consistently estimate the reimbursement effect.

states with a Certificate of Need program that applied to medical equipment purchases. Data on Certificate of Need programs are from the Intergovernmental Health Policy Project. Twenty-five states had a program for the entire period, and four states had a program for some of the period.

There are likely to be substantial disparities in the enforcement of these regulations across states. For example, New York's CON program is widely viewed as the most stringent. Because we do not have information on the intensity with which these program are applied, we use a simple indicator variable for the presence or absence of a program. Since more intensive Certificate of Need programs are likely associated with the state rate regulation noted above, we suspect that our rate setting variable picks up a more general "regulatory climate" rather than an effect specific to rate setting programs. We return to this issue below.

Malpractice pressure. Concerns about "defensive medicine" -- the use of medical treatments not worth their cost as a result of providers' fear of malpractice claims -- are cited as a potential cause of excessive medical expenditures (Office of Technology Assessment, 1994). Studies have suggested that "direct" reforms in malpractice liability -- caps or bans on damage awards, eliminating mandatory pre-judgment interest, or collateral source rule reform -- may lead to reductions in claims rates, malpractice insurance premiums, and medical spending, without adverse effects on patient outcomes (Danzon, 1986; Kessler and McClellan, 1996). We thus include a dummy variable for whether states had adopted a direct reform. This variable changes over time. In 1984, 43 percent of hospitals were in states with such a reform, while nearly 80 percent of hospitals were in a state with such a reform in 1991. In our models, we allow the malpractice reform variable to vary over time.

Provider Interactions. Interactions between providers may affect the diffusion of technology for several reasons. First, physicians may lobby hospital managers for technologies they are likely to use or may "induce demand" for procedures they perform. Past work has shown, for example, that specialists use intensive procedures related to their specialty more commonly than do general physicians (Greenfield et al., 1992). To proxy for this, we include the share of physicians in the area in 1985 (near the beginning of the sample) who were cardiologists or thoracic surgeons.[13] The average hospital is in an area where about 3 percent of physicians were cardiologists or thoracic surgeons.

Interactions among hospitals may also affect technology diffusion, although the direction of the effect is not clear. Some interactions between hospitals are likely to be competitive. If the fixed costs of technology acquisition are low and use of the technology is potentially high, for example, hospitals might engage in a "medical arms race" to acquire new technologies (Robinson and Luft, 1985). As the costs of acquisition rise or the volume of suitable patients falls, in contrast, the preemptive nature of other hospitals having acquired the technology may become more important.

A strict model of competition may not be the most appropriate for medical care, however. Medical professionalism encourages ongoing interactions between physicians and hospitals in the same area regarding new developments in practices. For example, teaching centers sponsor formal training in the use of new techniques that clinical investigators on their staff have developed, and smaller hospitals generally have established cooperative relationships with larger facilities to provide intensive treatments which the smaller hospital does not have the capability to perform. Specialists in a given geographic area also interact informally in the discussion of referred cases, at research

[13] As discussed below, we include a variable for the distance to a major teaching center, so that this variable is not just picking up whether the hospital is in an area with a substantial teaching ethic.

symposia, and in the observation of colleagues' techniques. These interactions may influence the diffusion of technology, although the direction of the effect is unclear. Being closer to teaching hospitals, for example, may convince non-teaching hospitals that they can transfer patients rather than acquire new technologies themselves, but they may also learn more rapidly that these technologies are very valuable.

To capture these interactions among hospitals, we include two variables: the share of other hospitals in the area that have already adopted the technology (weighted by the number of beds),[14] and the distance to the nearest major teaching center.[15] The "arms race" and learning theories suggests that a hospital will be more likely to acquire the technology when competitor hospitals have already done so and when it is nearer to a major teaching center. The preemption theory and cooperative treatment theory suggest that these factors will be negatively related to acquisition. The average hospital was in an area where 37 percent of hospital beds had the technology in 1991, and was nearly 200 miles from a major teaching center.

Demographic factors. The characteristics of the population served by a hospital may influence the services it chooses to provide. Income is strongly associated with receipt of medical care as is age. We thus include in our models the logarithm of median family income and the share of the

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[14]Since the share of other hospitals with the technology changes over time, we treat this variable as time-varying in our hazard models. If there were no other hospitals with at least 100 beds in the area, we set this variable to zero.

[15]We included the 14 cities with the largest number of interns and residents as major teaching centers: Ann Arbor, Baltimore, Boston, Chicago, Cleveland, Dallas/Fort Worth, Detroit, Los Angeles, New York, Philadelphia, Pittsburgh, St. Louis, San Francisco/Oakland, and Washington, D.C. To measure distance to a major teaching center, we treat each hospital as if it were at the geographic center of its zip code and measure the distance to the nearest hospital in a major teaching center.

population over age 65.

IV. Reduced Form Estimates of Angioplasty Diffusion

To analyze the relationship between these various factors and technology diffusion, we begin with reduced form estimates of the determinants of technological change. Since angioplasty is the newest intensive procedure, we focus on explaining the diffusion of that technology. Our regressions are of the form:

$$\begin{pmatrix} \textit{Share of Patients} \\ \textit{Receiving Angioplasty} \end{pmatrix}_{i,t} = X_{i,t}\beta + \epsilon_{i,t}. \qquad \textbf{(2)}$$

where i denotes hospitals and t denotes years. As before, we sort patients on the basis of hospital of initial admission. These regressions are reduced form in the sense that they do not separate the response into an acquisition decision and a decision about use conditional on acquisition.

Before presenting estimates of equation (2), several issues are worth noting. The first concerns the distinction between cross-section and time-series variation. While we have multi-year data on acquisition and use of technologies, we do not think the time dimension is the most interesting one. Rather, we are primarily interested in cross-sectional questions: do certain factors increase the probability that a hospital acquires the technology or the speed with which the technology is acquired? How do these factors affect the share of patients for whom the technology is used? In certain cases, we allow the independent variables to change over time (for example, as new legislation passes), but we are leery of using these data in a fixed-effects framework.

The second issue is the potential endogeneity of several of our variables. For example, cardiologists may choose to locate in an area because they know the population there values hightech medical treatment of heart attacks. Even the number and type of hospitals may be endogenous to technology acquisition. We have two responses to this concern. First, many of these endogeneity issues -- particularly those involving the public policy variables -- are likely to work *against* our finding any significant effects. For example, if states pass malpractice reform legislation because they believe past technology adoption was too rapid, our estimates would be biased toward a *positive* association between malpractice reform and technology acquisition. Findings that policy variables limit the diffusion of technology are therefore likely to be lower-bound estimates. Second, it may be more appropriate to think of these market variables as part of a system of responses. We are examining the effect of existing market characteristics, such as physician supply, on hospital technology adoption decisions. One could then couple this analysis with a model of how physician supply responds to technology diffusion. Our results begin to characterize this system.

A third concern is about unmeasured area effects that might influence all hospitals in a region similarly. If demand for angioplasty is high in an area, hospitals will be more likely to acquire the technology. This will be measured as an increase in the "competition" that a hospital faces, inducing a noncausal relationship between our measure of competition and technology acquisition. In linear models, one solution to this problem is to instrument for the ownership decision of other hospitals using the characteristics of those hospitals (Besley and Case, 1995).[16] In nonlinear models, such as our hazard model below, no equivalent instrumental-variables solution exists. We instead implement an analogous two-stage least-squares technique. In the first stage, we regress the competition variable each year on the other **x**'s for that hospital and the *average* **x**'s for

[16]The linear model may be expressed as $y = x\beta+\alpha \mathbf{W}y+\epsilon$, where y is an indicator for whether the hospital has the technology and **W** is a weighting matrix that assigns each hospital the average acquisition rate of the other hospitals in the area. This equation can be re-written as $y = (\mathbf{I}-\alpha\mathbf{W})^{-1}\cdot[x\beta+\epsilon]$, and α and β can be estimated using a Taylor series expansion.

the area as a whole. We then form the predicted values from this equation and use the predicted competition measure in our regressions. The identifying assumption is that the average **x**'s in the area as a whole should not affect a given hospital's decision to acquire the technology once we account for that hospital's characteristics. In practice, the variation in the average **x**'s in the area comes largely from variation in the bed size, teaching status, and ownership status of the other hospitals; these characteristics seem plausibly exogenous to a given hospital.

Table 5 presents our reduced form models of the share of patient receiving angioplasty in 1984 and 1991. We exclude hospitals in the District of Columbia (very high incidence of patient crossover from adjacent states, complicating our measurement of the factors influencing adoption) and in Hawaii and Alaska (extreme values for some of our technological-proximity measures). This leaves a final sample of 3,033 hospitals, of which roughly 2,900 have admissions in any given year.[17] The regressions are weighted by the share of patients admitted to each hospital. We include all of the explanatory variables discussed above, as well as seven dummy variables describing the hospital's MSA size category. In the first two columns, we also control for region dummy variables, to capture long-standing differences in technology utilization by region.

The region variables and city size variables (not reported) are significantly related to procedure use. Use was highest in the West and Rocky Mountain areas, and lowest in the Southeast. The MSA size effects suggest an inverse U-shape pattern of technology use. Use rates are highest in mid-size cities and then decline in the very largest and very smallest MSAs.

The first block of Table 5 shows coefficient estimates for the effects of hospital

[17]This sample of hospitals is the set for which summary statistics were reported in Table 4. We also estimated models excluding hospitals that closed or merged over the period and hospitals with few patients in some years. The results were very similar to those reported.

characteristics on angioplasty use. They accord well with expectations. Patients initially admitted to larger hospitals are more likely to receive the technology than are patients admitted to smaller hospitals. The difference in receipt among very large and very small hospitals increases from 1 percent in 1984 to 7 percent in 1991, which are large compared to the average procedure utilization rate (1 percent in 1984 and 12 percent in 1991). Patients initially admitted to government hospitals are somewhat less likely to receive angioplasty, but there is no significant difference in patients admitted to for-profit and teaching hospitals.

The second block shows the effect of the insurance variables on diffusion. The insurance variables are significantly related to the diffusion of technology. Two of the variables support the "profitability" hypothesis. Patients admitted to hospitals in states with rate regulation have lower use rates, and this difference is substantial -- over 3 percentage points in 1991. Increased managed care enrollment is also associated with less use of angioplasty in both years. A one standard deviation increase in HMO enrollment reduces angioplasty use by about .6 percentage points.

There is also some evidence for the "income effect" hypothesis, however. In areas with more uninsured, there is increased use of angioplasty in the elderly, by 1.5 percentage points per one standard deviation increase in uninsured. To the extent that income effects are operative, we would expect them on the uninsured more than for those with insurance.

The third block shows the effect of technology regulation on procedure use. Certificate of Need regulations reduce angioplasty use by about 1.6 percent in 1991. This effect is smaller than that of the Rate Regulation variable, particularly in 1991. As noted above, this might be due to the absence of reliable data on the stringency of review programs, leading our rate regulation variable to encompass a more general "regulatory climate".

The fourth block of the Table shows that malpractice reform is not related to use of angioplasty. The coefficient is small and statistically insignificant in both years.

The provider interaction variables, shown in the fifth block of the Table, are also related to diffusion. In areas with a greater share of cardiovascular physicians, more patients receive angioplasty, particularly in 1991. The coefficient implies that if the share of cardiovascular physicians were 1 standard deviation lower in 1991, utilization of angioplasty would have fallen by 0.5 percentage points. This is consistent with a model that specialists tend to use new technologies more aggressively. The hospital-interaction variables present a mixed story. Hospitals are more likely to use a procedure if other hospitals nearby have acquired it, but there is no effect of distance to a major teaching center on utilization. These results are partly but not fully consistent with the "arms race" or learning models. It is clear that neighboring hospitals' patterns of technology use are an important influence on technology use at a given hospital.

The coefficients on the demographic variables are mixed. Higher county income is associated with greater use of angioplasty, while a larger population share of the elderly is associated with less use. These variables thus do not tell a consistent story.

The regressions in the first two columns control for region effects. State factors may also be correlated with the diffusion of technology. For example, physician density varies across states and may be related to the physician specialty mix. If such unmeasured state variation is not captured with the regional dummy variables, it might bias the coefficients on the physician mix. To address this concern, we estimated the model including state dummy variables instead of region dummy variables. In this specification, we cannot include any of our state-level variables, including HMO enrollment, and indicators for rate regulation, Certificate of Need regulation, and malpractice reforms. However, we can investigate how the other coefficients are affected by including state effects.

These results are reported in the third and fourth columns of the Table. Most of the coefficients are almost identical in the specifications with region- and state-effects. The most noticeable difference is the coefficient on distance to a major teaching hospital, but even for this variable the difference is not substantial. Thus, in the rest of the paper we report results from models with region effects only.

Overall, our reduced form results suggest that the most important variables explaining the diffusion of technology are the generosity of insurance, technology regulation, and provider interactions.

V. Structural Estimates of Technology Diffusion

The reduced form estimates documented that factors like insurance generosity, public sector regulations, and provider interactions affect the use of technology. Those estimates did not differentiate between changes in acquisition probabilities and changes in use conditional on acquisition, however. For policy purposes, it is important to separate these two sources of changes in utilization. If there are fixed costs to acquiring technologies or learning curves in employing new technologies, for example, factors that reduce the number of hospitals acquiring a technology but increase use in each hospital with the technology will improve overall welfare. Indeed, concentrating the use of resources into larger groups has been one goal of technology regulation. The division between acquisition and use is also important in the incentives for technology development. Innovators of some technologies (such as radiological scanning equipment) receive revenue only when the technology is purchased, independent of how frequently it is utilized.[18] Thus, changes in

[18] This is not true for all technologies. For example, the developers of angioplasty catheters receive revenue from each sale, rather than the number of hospitals adopting the technology.

the number of hospitals acquiring the equipment, rather than total utilization, will affect the incentives to develop it. Finally, the general concern about "access" to health care for the uninsured is largely a question about whether the hospitals treating uninsured patients have the capability (and the financial resources) to provide high quality medical care to uninsured patients. If technological availability is concentrated in hospitals more likely to treat the insured, then access to intensive technologies for the uninsured will suffer, no matter how frequent such use is for the insured. To analyze these issues, we need to separate the effects on procedure use into changes in the acquisition probability and changes in use conditional on acquisition. We do this in this section.

V.A. The Technology Acquisition Decision

We begin with the decision of hospitals to acquire angioplasty capability. Since we have longitudinal data on hospital technology adoption for an 8 year period, a natural model of ownership is a hazard model (Rose and Joskow, 1990). Denoting the cumulative probability that a hospital has angioplasty at time t as $F_i(t)$ and the density function at time t as $f_i(t)$, the hazard is the probability that a hospital acquires the technology at time t conditional on not having acquired the technology up to that point: $\lambda_i(t) = f_i(t)/[1-F_i(t)]$. We specify a proportional hazard model for technology adoption: $\lambda_i(t) = exp(x_i(t)\beta) \cdot \lambda_0(t)$, where $x_i(t)$ is the (potentially) time varying proportional hazard and $\lambda_0(t)$ is the baseline hazard. Denote $\gamma(t) = \ln(\int_{t-1}^{t} \lambda_0(s)\, ds)$, the logarithm of the integrated baseline hazard from $t-1$ to t. Then, if the $x_i(t)$ variables are constant within a period, the cumulative acquisition probability is given by:

$$F_i(t) = 1 - \exp\left(-\sum_{s=1}^{t} \exp(x_i(s)\beta + \gamma(s)) \right). \tag{3}$$

We estimate the baseline hazard (γ_s) semi-parametrically, as in Meyer (1990) and Cutler (1995).

The probability that a hospital acquires the technology during period t_i^* is $F_i(t_i^*)-F_i(t_i^*-1)$. The probability that a hospital has not acquired the technology as of the end of the sample (T) is $1-F_i(T)$. Denoting c_i as an indicator for the hospital being censored, the likelihood function for the data is:

$$L = \prod_{i=1}^{N} [F_i(t_i^*) - F_i(t_i^* - 1)]^{1-c_i} \, [1 - F_i(T)]^{c_i}. \tag{4}$$

We maximize the logarithm of the likelihood using standard techniques.

The first column of Table 6 presents results of hazard models for the diffusion of angioplasty. The estimated effects of hospital-specific factors are qualitatively similar to those in the reduced form models. Larger hospitals and teaching hospitals have much higher adoption hazard rates, and government hospitals have lower hazard rates. All of these results are statistically significant.

The remaining blocks show the coefficients on the policy and market variables. Two sets of variables are most important in explaining technology acquisition: insurance generosity, and the provider interactions. As the second block shows, the insurance variables have substantial effects on technology adoption: areas with high HMO enrollment or with rate regulation are less likely to adopt angioplasty. There is no effect of the percent uninsured on technology ownership.

To evaluate the magnitude of these coefficients, Table 7 shows simulations of technology utilization under different assumptions. The first column shows the overall change in technology utilization in 1991 implied by the reduced form models in Table 5. For example, holding HMO enrollment constant at its 1991 level would have increased the rate of angioplasty utilization in 1991 from 13.6 percent to 14.1 percent. The second column shows the change in the share of hospitals predicted to have the technology, given by the hazard models. Relative to the 31.4 percent of hospitals with angioplasty in 1991, if HMO enrollment had been constant at its 1984 level, an additional 2.2 percent of hospitals would have invested in angioplasty. And if rate regulation had been imposed in all states, 7.8 percent fewer hospitals would have invested in angioplasty.

Since patients who are initially admitted to hospitals with angioplasty are more likely to receive the procedure than patients initially admitted to hospitals without the technology, this increase in procedure availability will increase overall utilization rates. The magnitude of this effect is shown in the third column of the Table; given the average rate of utilization in hospitals with and without the procedure, if HMO enrollment had remained at its 1984 level, an additional 0.2 percent of patients would have received the procedure. And if rate regulation were imposed in all states, 0.7 percent fewer patients would receive the procedure. Relative to the change in total utilization given in the first column, the changes resulting from HMO enrollment and rate regulation are 25 percent (0.7 percent/2.8 percent of the change for rate regulation) to 40 percent (0.2 percent/0.5 percent of the change for HMO enrollment) of the total effect on utilization.

The second important variables are the provider interactions. A higher proportion of cardiovascular physicians in an area is associated with significantly earlier adoption, consistent with the models of lobbying or induced demand. A one standard deviation reduction in the share of cardiovascular physicians in an area would reduce the share of hospitals with the technology by 3.5 percentage points and would reduce procedure rates by 0.3 percentage points, about 60 percent of the total change in utilization resulting from this variable. The hospital variables are again mixed. Increased shares of other hospitals with the technology also increase diffusion, but so does moving a hospital *farther* from a major teaching center. Thus, it appears that no simple story can explain the coefficients on hospital variables.

The other variables are insignificantly related to adoption or have negative effects on adoption (as with the share of the elderly). The overall conclusion is that in understanding technology acquisition, the most important measures are insurance and provider effects. These variables significantly influence the acquisition decision, which is about half of the overall effect.

V.B. Use Conditional on Ownership

The second part of diffusion is the extent to which technology is utilized once it has been acquired. Since the same factors may affect hospitals with the technology differently from hospitals without the technology, we specify the conditional use equation separately for patients admitted to each type of hospital:

$$\begin{pmatrix} \textit{Share of Patients} \\ \textit{Receiving Procedure} \end{pmatrix}_{i,t} = \begin{pmatrix} x_{i,t}\beta^{o} + \epsilon^{o}_{i,t} & \textit{if own} \\ x_{i,t}\beta^{n} + \epsilon^{n}_{i,t} & \textit{if not own} \end{pmatrix}. \tag{5}$$

As is well known, estimating equation (5) separately for hospitals that have and have not acquired the technology may lead to biased estimates if the hospitals whose ownership decision is affected by the $\mathbf{x}$ variables differ in their underlying propensity to use the technology. If we had an instrument that influenced hospitals' adoption decision but did not affect how frequently they used the technology, we could condition on the exogenous dimension of technology acquisition and estimate equation (5) for those hospitals. We suspect, however, that there are no instruments for acquisition that would not also affect technology utilization. Thus, there are no natural instruments for this equation.

In the absence of an instrument, we estimate equation (5) with a sample selection correction

(Heckman, 1979).[19] It is important to recognize that our estimates of β depend on our choice of parameterization for the maximum-likelihood model and are identified only because of non-linearities in the equations for acquisition and conditional use. In contrast, there is no selection-bias problem for the decision to acquire technology, since the sample of potential acquirers (the universe of hospitals) is fixed. For this reason, we have more confidence in our models for technology acquisition than in our models for use conditional on ownership.

The remaining columns of Table 6 present estimates of the effect of our policy and market factors on the decision to use angioplasty in hospitals with angioplasty (column 2) and hospitals without angioplasty (column 3). We pool all 8 years of data in estimating equation (5) and include year dummy variables, so that our total sample is nearly 20,000 hospital-years.[20] The last row of the Table shows the coefficient on our sample selection variable. We find evidence of selection for adopters but not for non-adopters; hospitals that use the procedure more are more likely to acquire the technology than the hospitals that would use it less frequently.

The insurance variables are strongly related to technology use, generally with larger effects for adopters than nonadopters. In several cases, these variables reinforce the estimates in the

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[19] Our correction is slightly non-standard since our first-stage equation is non-linear. Note that the hazard model can be rewritten as:

$$z(t_i) = \log\left(\int_0^{t_i} \lambda_i(s,X,\beta)\, ds \right) = u_i$$

where u_i has Type I extreme value distribution, with cumulative distribution function F(.). We define $u^*_i = \Phi^{-1}[F(u_i)]$, so that u^* is a normally distributed error corresponding to u. Our selection correction is based u^* rather than u. In particular, if the hospital acquired the technology in year t_i, we know that $z(t_i-1) < u_i < z(t_i)$, or that $\Phi^{-1}[F(z(t_i-1))] < u^*_i < \Phi^{-1}[F(z(t_i))]$. The expectation of the error term is the conditional mean of u^*_i.

[20] We correct the standard errors for inter-hospital correlation.

acquisition equations. Increased HMO enrollment not only lowers adoption; it also reduces utilization of the technology. The same is true for the imposition of rate setting. As Table 7 shows, these effects are a bit larger than the effect resulting from changes in acquisition rates, but of the same order of magnitude.

The uninsurance rate is positively related to technology utilization, particularly in hospitals that have acquired the technology. This is what would be predicted from the "income effect" hypothesis. Thus, there is some evidence for the income effect hypothesis, as well as strong evidence for the profitability hypothesis.

The next block shows that Certificate of Need regulation has a negative effect on use, for both adopters and non-adopters. The magnitude of this effect is roughly comparable to that for rate regulation.

The provider interactions typically have much smaller effects on use conditional on acquisition than they do on the probability of acquisition, and the statistical power of these estimates is generally much smaller. Increased shares of cardiovascular physicians are associated with offsetting effects on transfers to receive the procedure at nonadopting hospitals and use of the procedure in adopting hospitals. And the measures of competition and distance from a teaching hospital are essentially unrelated or negatively related to use of the procedure.

Finally, increased income is associated with a greater likelihood that people admitted to hospitals without angioplasty capability will ultimately receive it, by roughly 0.5 percentage points for a one standard deviation increase in income. The share of the elderly population does not significantly affect conditional procedure rates.

Overall, the most important variables explaining technology use once it has been acquired are the insurance generosity and regulations on technological availability.

VI. Ownership, Financial Incentives, and Technology Diffusion

Our models so far have not allowed for differential responses across hospital types to the determinants of technological change. Examining differences across hospital types is important, however. Different hospitals have very different clienteles. Public hospitals are disproportionately likely to serve the indigent, for example, while for-profit hospitals have wealthier, better-paying patients. As policy or market factors change, public hospitals may be affected very differently from for-profit hospitals, with important effects on access to medical care. In this section, we examine how financial factors differentially affect non-profit, for-profit, and government hospitals. The public concern about care for the uninsured largely concerns access issues: are the uninsured being treated at hospitals with the same technological capability as the insured? If the hospitals have different capabilities, how different are they? The focus on access to resources suggests that we worry particularly about the availability of technology in different hospitals rather than the use conditional on availability.

The natural way to examine these access issues is to estimate our hazard models for technology acquisition separately for for-profit, not-for-profit, and government hospitals. There are not enough for-profit hospitals (364 hospitals) and government hospitals (386 hospitals), however, to estimate such models precisely. Consequently, we instead interact the dummy variables for for-profit and government hospitals with our measures of insurance generosity and examine instead the more limited question of how insurance variables differentially affect these different hospitals. Implicitly, this imposes constancy of the other coefficients across types of hospitals.

Table 8 shows models for the acquisition of angioplasty where the financial variables are interacted with ownership status of the hospital. All of the other variables are the same in this Table as in Table 6; for convenience, we report only the direct effects of government and for-profit status on diffusion, and the interaction terms. Because there are so few for-profit hospitals in states with rate setting (17 in total), we omit this interaction.

The estimates suggest two important differences in how insurance generosity affects different hospitals. First, private, not-for-profit hospitals and government hospitals are more sensitive to the presence of HMOs than are for-profit hospitals. Indeed, the estimates suggest that HMOs have no effect on for-profit hospitals, and have a roughly equal effect on public hospitals and private, not-for-profit hospitals. This is consistent with the theory that increased HMO enrollment will shift the distribution of resources towards for-profit hospitals and away from non-profit and government hospitals.

Perhaps more importantly, the uninsurance rate has a significant negative impact on technology acquisition in for-profit and particularly government hospitals, while it does not affect acquisition by private, not-for-profit hospitals. A government hospital in an area with an uninsured population share that is one standard-deviation larger than average has hazard rates for technology adoption about 40 percent lower than in private, not-for-profit hospitals. This result is concerning, because of the increasing tendency for the uninsured to receive care in public rather than private hospitals over time. Should this trend persist, it suggests that the availability of care for the uninsured may fall over time relative to care for the insured.

VII. Conclusion

In this paper, we examine the diffusion of technology for treatment of heart attacks. Between 1984 and 1991, the cost of a heart attack rose 4 percent annually in real terms. We first show that the dramatic expansion of intensive cardiac surgeries accounts for essentially all of the growth in treatment costs. In contrast, the real price of heart attack treatments has been nearly constant.

We then examine at a micro level the sources of this technology diffusion. We find that insurance generosity, technology regulation, and provider interactions have the most important effects on the diffusion of technology. These variables affect the diffusion of technology through both changes in the share of hospitals that acquire the technology and changes in the share of patients who receive it once it has been acquired.

Our results are valuable in that they examine a specific disease where it is possible to learn about the technologies involved in great detail without resorting to a technology "residual". Where our results are most tentative, however, is that they are evidence for only one type of technology. It would be useful to examine other technologies where the institutional and reimbursement environment varies more to determine how different policy and market factors affect diffusion more broadly. We leave this as a topic for future research.

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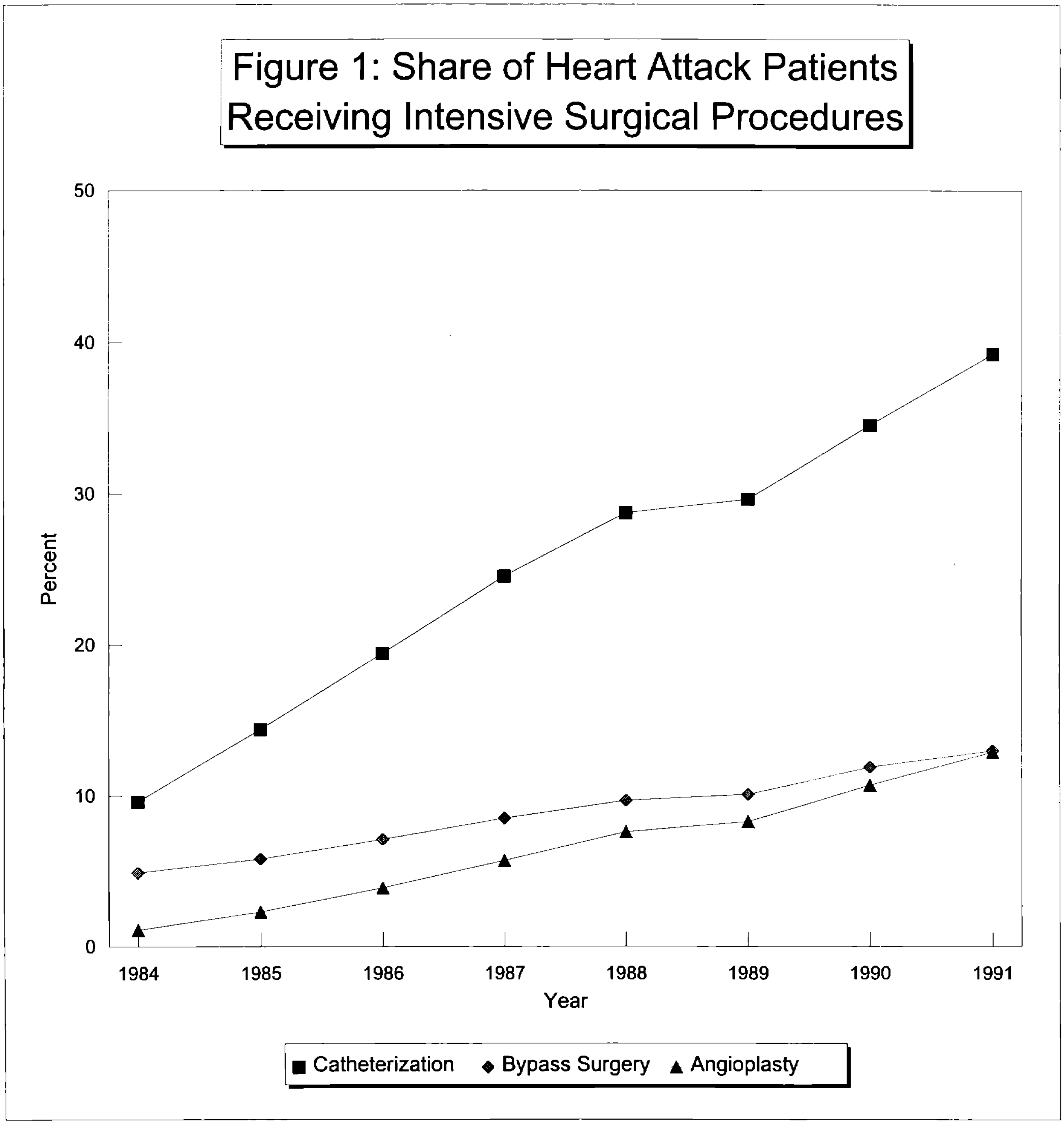
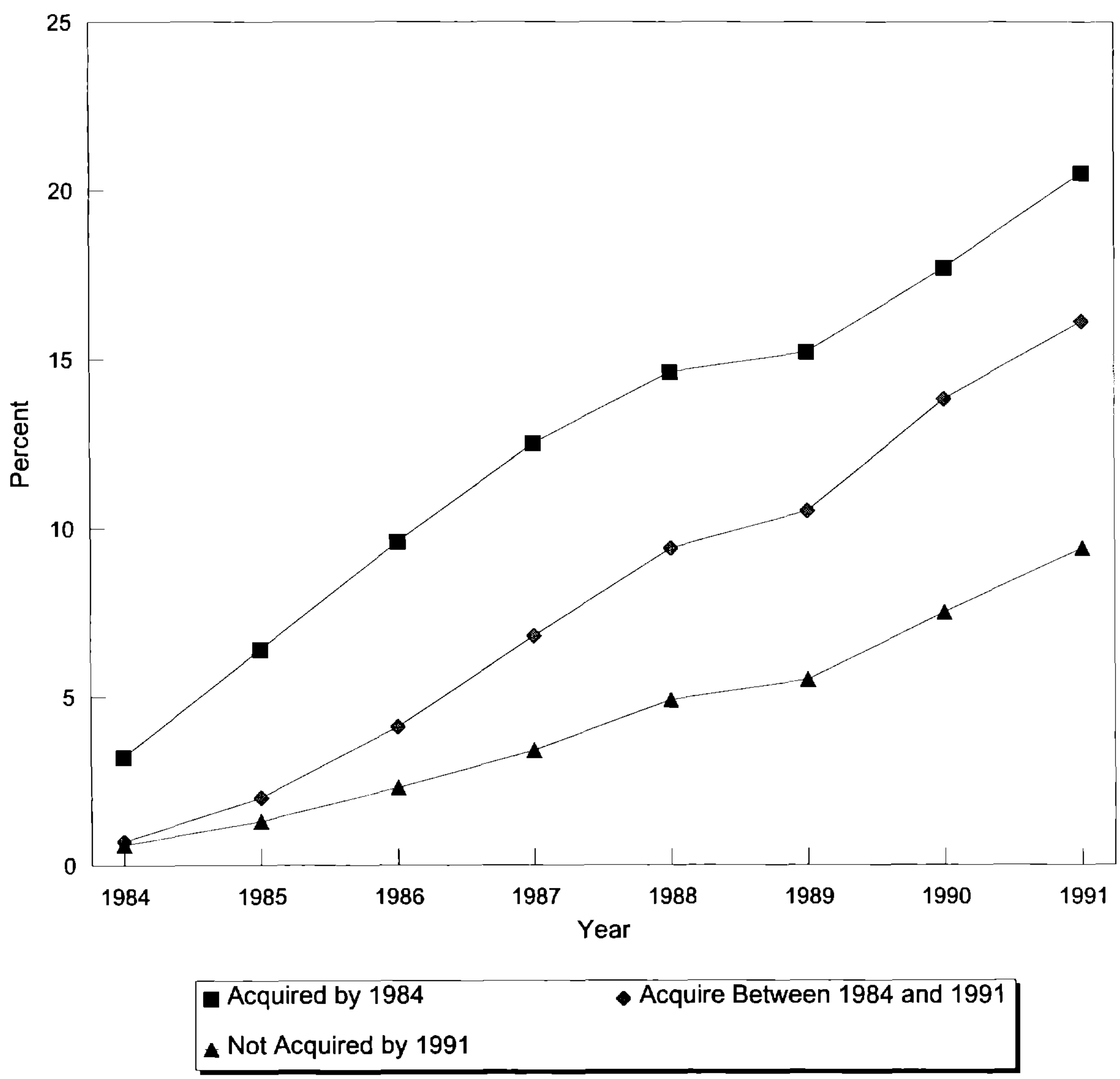


Figure 1: Share of Heart Attack Patients Receiving Intensive Surgical Procedures
50
40
30
20
10
0
Percent
1984
1985
1986
1987
1988
1989
1990
1991
Year
Catheterization
Bypass Surgery
Angioplasty

Figure 2: Use of Angioplasty By Hospital of Initial Admission



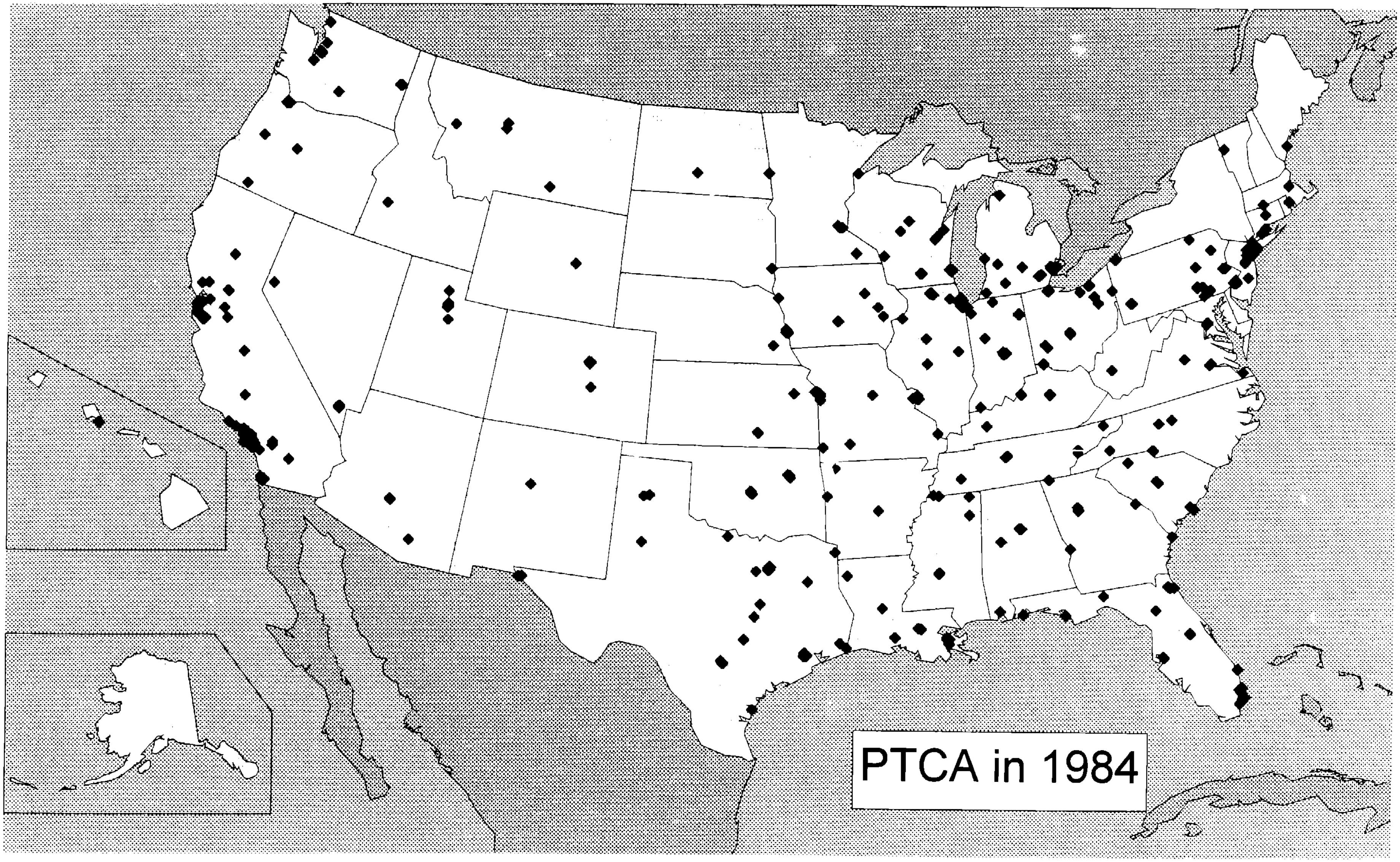

PTCA in 1984

Table 1: Technological Change and Reimbursement in Cardiac Procedure Use, 1984-91

	Intensive Procedure Use			Average Hospital Reimbursement		
AMI Treatment	1984	1991	Annual Change*	1984	1991	Annual Change
Average Reimbursement				$11,175	$14,772	4.0%
Type of Treatment						
Medical Management	88.7%	59.4%	-4.2%	$9,829	$10,783	1.3%
Catheterization Only**	5.5	15.5	1.4	15,380	13,716	-1.6
Angioplasty	0.9	12.0	1.6	25,841	17,040	-5.9
Bypass Surgery	4.9	13.0	1.2	28,135	32,117	1.9
Price Index				$14,981	$14,772	-0.2%
Quantity Index				$12,047	$14,772	2.9%

Note: Reimbursement for 1984 is in 1991 dollars, adjusted using the GDP deflator. Price and quantity indices use 1991 weights.

* Growth is average percentage point change each year.

** Patients who received catheterization but no revascularization procedure. Patients who received bypass surgery or angioplasty will also have had a catheterization.

Table 2: Sources of Increase in Intensive Procedure Use for Heart Attack Patients, 1984-1991

Source	Procedure		
	Cardiac Catheterization	Bypass Surgery	Angioplasty
Share of Hospitals with Technology			
1984	20.9%	10.6%	8.2%
1991	40.6	16.8	18.2
Share of Increase In Procedure Use Resulting From:			
Acquisition of Technology	15.4%	7.8%	18.9%
Increased Use Among Hospitals With Procedure	64.3	34.1	42.6
Increased Use Among Hospitals Without Procedure	27.0	59.4	47.9

Note: Last block does not add to 100 percent because of covariance between changes in use rates and share of patients.

Table 3: Distribution of AMI Patients and Technologies by Hospital Size, 1991

Bed Size	Number of Hospitals	Average Number of Patients	Share of Hospitals With Technology: Cardiac Catheterization	Bypass Surgery	Angioplasty
Total	5,253	174	40.6%	16.8%	18.2%
<100	2,371	45	7.4	0.3	0.5
100-199	1,090	134	43.6	4.7	7.5
200-299	685	245	69.5	21.8	23.8
300-399	450	348	86.0	41.1	44.7
400-599	430	450	93.0	67.7	69.1
600+	227	626	96.0	88.5	89.0

Note: The sample is hospitals with at least one admission for AMI in 1991.

Table 4: Predictions About the Factors Influencing Technology Diffusion

Variable	Predicted Effect	Level of Aggregation	Mean	Standard Deviation
Hospital Controls				
For-Profit	-	Hospital	15.4%	36.4%
Government	-	Hospital	15.7%	36.4%
Teaching	+	Hospital	15.5%	36.2%
Insurance				
Percent Uninsured	- if profitability or practice pattern effects + if use to offset other losses	MSA/Rest of State	13.6%	6.0%
HMO Enrollment	- if profitability or practice pattern effects + if use to offset other losses	State	13.3%	8.5%
Rate Regulation	- if profitability or practice pattern effects + if use to offset other losses	State	16.7%	37.3%
Technology Regulation				
Certificate of Need	-	State	63.2%	48.2%
Malpractice Reform				
Direct Reform	-	State	79.8%	40.2%
Provider Interactions				
Percent Cardiovascular Physicians	+	MSA/ County	2.7%	1.3%
Share of Other Hospitals In area with Technology	+ if "arms race" or learning effects - if preemption or substitute transfers	Hospital	38.2%	30.0%
Distance to Major Teaching Center	- if "arms race" or learning effects + if preemption or substitute transfers	Hospital	191	227
Demographics				
Log(Median Income)	+	MSA/ County	9.9	.16
Share Over 65	+	MSA/ County	11.3%	3.1%

Note: Summary statistics are for hospitals with at least 100 beds. Means for Rate Regulation and Certificate of Need Regulation are for 1984. Means for HMO Enrollment, Malpractice Reform, and Share of Other Hospitals with Angioplasty are for 1991. The sample excludes hospitals in Alaska, Hawaii, and the District of Columbia. There are 3,033 observations.

Table 5: Reduced Form Models for the Share of Patients Receiving Angioplasty

	Region Controls		State Controls	
Variable	1984	1991	1984	1991
Hospital Controls				
200-299 Beds	.003*	.016**	.002*	.017**
	(.001)	(.005)	(.001)	(.005)
300-399 Beds	.004**	.030**	.004**	.029**
	(.001)	(.005)	(.001)	(.005)
400-599 Beds	.006**	.044**	.007**	.043**
	(.001)	(.005)	(.001)	(.005)
>600 Beds	.013**	.068**	.014**	.068**
	(.002)	(.006)	(.002)	(.006)
For-Profit	-.002	.004	-.002	.002
	(.002)	(.006)	(.002)	(.006)
Government	-.003*	-.009*	-.003**	-.010**
	(.001)	(.005)	(.001)	(.005)
Teaching	-.001	.002	-.001	.004
	(.001)	(.004)	(.001)	(.004)
Insurance				
Percent Uninsured	.016	.244**	.012	.232**
	(.012)	(.041)	(.014)	(.047)
Percent in HMOs	-.068**	-.068*	---	---
	(.018)	(.042)		
Rate regulation	-.003*	-.033**	---	---
	(.002)	(.006)		
Technology Regulation				
Certificate of Need	-.004**	-.016**	---	---
	(.001)	(.005)		
Malpractice				
Direct Reform	-.001	.006	---	---
	(.001)	(.005)		

Table 5 (continued)

Variable	Region Controls 1984	Region Controls 1991	State Controls 1984	State Controls 1991
Provider Interactions				
Percent Cardiovascular Physicians	.046	.410**	.053	.426**
	(.046)	(.153)	(.047)	(.160)
Share of Other Hospital Beds in Area with Technology	.013**	.029**	.014**	.031**
	(.005)	(.012)	(.005)	(.013)
Distance to Nearest Major Teaching Center	.000004	-.000014	.000007	-.000031
	(.000003)	(.000011)	(.000007)	(.000025)
Demographics				
Log(Median Income)	.012**	.059**	.006	.048**
	(.005)	(.016)	(.005)	(.017)
Percent of Population 65+	-.048**	-.119**	-.051**	-.138**
	(.018)	(.062)	(.021)	(.070)
Summary Statistics				
N	2,934	2,804	2,934	2,804
R^2	.155	.269	.217	.297

Note: The table reports regressions for the share of patients receiving angioplasty in 1984 and 1991. The share of other hospital beds in the area with the technology is instrumented for using the average **X**'s for other hospitals in the county. The sample is hospitals with at least 100 beds. The regressions are weighted by the number of AMI patients in the hospital. All regressions include 7 dummy variables for city size. The first two regressions include 9 region dummy variables; the second two regressions include 48 state dummy variables. Standard errors are in parentheses.
* Statistically significantly different from zero at the 10 percent level.
** Statistically significantly different from zero at the 5 percent level.

Table 6: Effects of Policy and Market Variables on Ownership and Use of Angioplasty

Independent Variable	Ownership (Hazard)	Use of Procedure (OLS) With Technology	Use of Procedure (OLS) Without Technology
Hospital Controls			
200-299 Beds	1.353**	-.024*	.002
	(.138)	(.015)	(.003)
300-399 Beds	2.210**	-.031*	.003
	(.138)	(.017)	(.004)
400-599 Beds	2.989**	-.044**	.004
	(.138)	(.020)	(.006)
>600 Beds	3.889**	-.048**	.003
	(.156)	(.024)	(.008)
For-Profit	.103	-.006	.000
	(.118)	(.008)	(.002)
Government	-.773**	.018**	.000
	(.106)	(.008)	(.002)
Teaching	.557**	-.016**	.000
	(.085)	(.007)	(.002)
Insurance			
Percent Uninsured	-.614	.237**	.046**
	(.889)	(.075)	(.016)
Percent in HMOs	-3.832**	-.115	-.069**
	(1.086)	(.073)	(.017)
Rate regulation	-.603**	-.014*	-.011**
	(.158)	(.008)	(.002)
Technology Regulation			
Certificate of Need	-.141	-.017**	-.008**
	(.100)	(.007)	(.002)
Malpractice			
Direct Reform	-.087	.010*	.000
	(.088)	(.006)	(.001)

Table 6 (continued)

Independent Variable	Ownership (Hazard)	Use of Procedure (OLS) With Technology	Use of Procedure (OLS) Without Technology
Provider Interactions			
Percent Cardiovascular Physicians	17.866**	-.512*	.143**
	(4.082)	(.301)	(.054)
Share of Other Hospital Beds in Area with Technology	.632**	.040	-.005
	(.293)	(.025)	(.005)
Distance to Nearest Major Teaching Center	.00074**	-.000015	-.000011**
	(.00024)	(.000017)	(.000004)
Demographics			
Log(Median Income)	-.456	.029	.037**
	(.370)	(.026)	(.005)
Percent of Population 65+	-6.627**	-.049	.037
	(1.643)	(.108)	(.030)
Selection Correction	---	.014**	-.002
		(.007)	(.004)
Summary Statistics			
N	3,033	5,971	17,164
log(Likelihood) / R^2	-2,581.09	.360	.412

Note: The table shows two-stage least squares estimates of hazard models for the diffusion of heart attack technologies. The share of other hospital beds in the area with the technology is instrumented for using the average **X**'s for other hospitals in the county. The sample is hospitals with over 100 beds. All models have dummy variables for 9 regions and 7 city sizes. The models for the use of technology have year dummy variables as well. Regressions for use of procedure are weighted by the number of AMI patients in the hospital. Standard errors in use equations are corrected for inter-hospital correlation.

* Statistically significantly different from zero at the 10 percent level.

** Statistically significantly different from zero at the 5 percent level.

Table 7: Effects of Policy and Market Factors on the Diffusion of Angioplasty, 1991

			Change in Utilization Resulting From:	
Change in Utilization Resulting From:*	Change in Total Use	Change in Ownership	Change in Ownership	Change in Use|Ownership
Baseline	13.6%	31.4%		
Insurance				
Reduce Percent Uninsured#	-1.5	0.6	0.0	-0.8
Freeze HMO Enrollment at 1984 Level	0.5	2.2	0.2	0.6
Impose Rate Setting in All States	-2.8	-7.8	-0.7	-1.0
Technology Regulation				
Eliminate Certificate of Need Regulation	0.9	1.3	0.1	0.7
Malpractice Reform				
Eliminate Malpractice Reforms	-0.5	0.9	0.1	-0.3
Provider Interactions				
Reduce Cardiovascular Physician Share#	-0.5	-3.5	-0.3	0.2
Increase Share of Hospitals with Technology	0.8	3.0	0.3	0.4
Move Hospitals Away From Teaching Center^	-0.3	2.0	0.2	-0.2
Demographics				
Increase Median Income	0.9	-1.2	-0.1	0.5
Increase Share Over 65	-0.4	-3.3	-0.3	0.0

Note: The table shows the effect of policy and market factors on the use of angioplasty.
* Change is one standard deviation unless otherwise noted.
# The share is assumed not to fall below zero.
^ Applies to hospitals not in a major teaching center.

Table 8: Financial Incentives and Ownership in the Diffusion of Angioplasty

	Ownership		
		Additional Effect For:	
Variable	Private Not-for-profit	For-Profit	Government
Hospital Controls			
For-Profit		.428	
		(.321)	
Government		.315	
		(.312)	
Insurance			
Percent Uninsured	.700	-3.241**	-6.354**
	(.991)	(1.673)	(1.778)
Percent in HMOs	-3.535**	2.470**	-1.648
	(1.104)	(1.284)	(1.240)
Rate regulation	-.668**	---	.243
	(.167)		(.347)
Summary Statistics			
N		3,033	
log(Likelihood)		-2,569.95	

Note: The table shows two-stage least squares estimates of hazard models for the diffusion of angioplasty. The specification is similar to Table 7, with the exception of the indicated interaction terms for for-profit and government hospitals. There are not enough for-profit hospitals in states with rate setting to estimate that coefficient reliably. Standard errors are in parenetheses.

* Statistically significantly different from zero at the 10 percent level.

** Statistically significantly different from zero at the 5 percent level.