

Diffusion and Productivity Growth in Health Care

Preliminary – not for attribution or quotation

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We examine productivity in the treatment of heart attacks across hospitals and over time. A model is developed that allows for physicians' (optimal) search over new technological innovations, and test the model with U.S. Medicare data on survival and factor inputs for 2.8 million heart attack patients during 1986-2004. We find that the speed of adopting highly efficient and often low-cost innovations such as β blockers, aspirin, and primary reperfusion explains a large fraction of variations in productivity, and swamps the impact of traditional factor inputs. The empirical patterns are also consistent with those found in macroeconomic cross-country studies: the persistence of rapid or slow adoption within institutions, a lack of convergence in output, substantial differences in long-run productivity, and the importance of a productivity "frontier." Large informational barriers to adoption are the best explanation for why some physicians fail to prescribe even aspirin for their patients, and could also explain puzzling empirical patterns in other sectors of the economy.

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1. Introduction

The idea that differential adoption of new technologies can explain variations in productivity across regions is by now well accepted in the macroeconomics literature. Parente and Prescott (1994) found that surprisingly small differences in the rates of technological adoption could imply large disparities in country levels of income. Similarly, Eaton and Kortum (1999) estimated that a large fraction of OECD productivity growth occurred through the international diffusion and adoption of new technology. Their results suggested that countries realized just two-thirds of the potential productivity gains (relative to autarky) because of the slow diffusion and adoption of ideas across borders.

There is a parallel literature in medicine documenting similar lags in adoption, and with similar adverse effects on overall productivity. For example, despite powerful evidence from a 1601 experiment demonstrating the effectiveness of lemon juice in preventing scurvy, the British Navy did not require foods containing vitamin C until 1794 (Berwick, 2003).¹ Yet during the 18th century, more men in the British Navy died of scurvy than were lost to battle casualties (Lee, 2004). More recently, β blockers, drugs costing pennies per dose, were shown during the early 1980s to reduce mortality following a heart attack by as much as 25 percent (Yusuf, et. al., 1985). Yet by

¹ In his 1601 voyage to India, Captain James Lancaster fed sailors in one of his ships 3 teaspoons of lemon juice every day, while in the other three ships, no lemon juice was provided. By the midpoint of the journey, 110 of the 278 sailors in the control group had died of scurvy (40 percent), while *none* of the sailors in the treatment group had been affected. Despite additional clinical evidence, and the remarkable results from Captain Cook's circumnavigation in 1768-71, in which citrus fruits and sauerkraut avoided any cases of scurvy, the British Navy did not set dietary regulations until 1794.

2000/2001, the median state-level use of β Blockers among appropriate patients was still only 68 percent (Jencks, 2003).

In this paper, we first develop a model where output depends on factor inputs (capital and labor services) and technology used in the hospital. The firm (or hospital) seeks to maximize the social value of lives saved minus resource and learning costs. To better understand differences across hospitals in both the speed of adopting specific and highly effective technology, we consider a search model where physicians face differing marginal costs of search to learn about new technologies. Physicians may be innovators, learning from primary scientific evidence (or their own colleagues), or imitators, learning from outside their institution (Bass, 1969). The nature of the search process has testable empirical implications, and yields estimates of the implicit informational barriers that must, in equilibrium, be facing physicians who are slow to adopt new and effective innovations.

We apply this model to the hospital-level treatment of patients diagnosed with a heart attack, or more precisely, with acute myocardial infarction (AMI). Past studies of health care productivity have focused on heart attacks because of the accuracy with which the diagnosis is identified, the importance of survival as an endpoint, and the cascade of new innovations in the treatment of AMI during the past several decades (e.g., Cutler et. al. 1998; Cutler and McClellan, 2001; Cutler, 2004).² We examine empirically three major innovations in the treatment of AMI – aspirin, β blockers, and reperfusion within 12 hours of the heart attack. (Reperfusion consists *either* of thrombolytic “clot-

² There is another literature measuring hospital efficiency, but these typically focus on costs per hospital day rather than on survival or other health outcome. See for example Chirikos and Sear (2000) and references therein.

busting” drugs, or surgical angioplasty.) These treatments are distinguished by the following unique characteristics: (a) well-established scientific evidence that the treatment saves lives, (b) a lack of serious financial barriers to adoption,³ and (c) the adoption decision is made by the physician, not by the supine heart attack patient.

We test the model using a sample of 2.8 million heart attack patients drawn from the fee-for-service Medicare population during 1986-2004, combined with detailed chart review information about adoption of the three innovations during 1994/95. Hospitals are further categorized into quintiles based on their propensity to adopt these effective treatments. The most striking result is that these quintiles of technology adoption explain large variations across hospitals in risk-adjusted survival, far larger than what can be explained by differences in expenditures either across hospitals or over time.

The empirical patterns of hospital productivity are remarkably similar to those found in countries. Like Comin and Hobijn (2004), who study country-level data, we find that hospitals with rapid diffusion in one highly effective technology are most likely to adopt other technologies. As well, we find no evidence of convergence; hospitals that are initially high-quality are just as likely to be high-quality after nearly two decades, and if anything there is some evidence of divergence through the early 2000s.

And like Eaton and Kortum (1999), we find substantial lags in the extent to which some hospitals lag behind others, with a steady-state gap of more than 3 percentage points in survival between the highest (or “frontier”) diffusion hospitals compared to the slowest diffusion hospitals, nearly one-third of the overall improvement in outcomes during the 1986-2004 period. The time-series patterns are roughly consistent with a

³ For hospitals facing financial barriers, thrombolytics provide nearly all of the potential benefits relative to angioplasty.

technology “frontier” model as in Nelson and Phelps (1966), but there is some suggestion too of an imitation or contagion effect, although the results are very sensitive to model specification.

One nagging question is: why are some physicians so slow to adopt? Unfortunately, none of the economist’s standard models is much help in explaining the slow adoption rates. When aspirin and β blockers cost pennies and all physicians have had at least 20 years of education, it’s difficult to harness models relying on heterogeneity in profitability (Griliches, 1957), acquired skills in the old technology that precludes adoption of the new (Jovanovic and Nyarko, 1996), complementarities between adoption and human capital (Nelson and Phelps, 1966) or technological growth favoring skilled workers (Caselli and Coleman, 2006). Instead, the patterns we observe can really only be rationalized by remarkably high implicit informational or search costs, generated either by very high discount rates (as in a model of procrastination), or barriers to learning about new technologies when looking at blueprints or reading an article about β blockers just isn’t enough (Keller, 2004)). Indeed, these informational barriers to adoption might have been viewed forty years earlier as evidence of “X-inefficiency” (Leibenstein, 1966).

2. The Model

In this section, we develop a simple model of hospital productivity that distinguishes between inputs that require substantial contributions of capital and labor (e.g., hospital bed-day or surgical procedures) and technology innovations where barriers are unlikely to arise solely from financial constraints.

Suppose that medical care per patient (e.g. quantity of medical services) at hospital i in year t (mc_{it}) is produced with constant returns technology:

$$(1) \quad mc_{it} = A_{it} l_{it}^{\varphi} k_{it}^{1-\varphi}$$

where l_{it} and k_{it} represent labor and capital inputs per patient, and A_{it} captures the technology in use at hospital i in year t . While it seems reasonable to assume constant returns for producing medical care (doubling staff and beds at a hospital can produce twice the number of admissions), we presume that medical care per patient has declining returns in terms of patient survival (or quality adjusted life years). We assume a particularly simple form for the relationship between survival per patient (y_{it}) and medical care per patient:

$$(2) \quad y_{it} = \beta \ln(mc_{it}) = \beta \ln(A_{it}) + \beta\varphi \ln(l_{it}) + \beta(1-\varphi)\ln(k_{it})$$

In this specification, the marginal return to medical care is declining, with $\partial y_{it} / \partial mc_{it} = \beta / mc_{it}$. The linearly separable form of equation 2 is convenient for what follows because the marginal product of labor and capital (in terms of survival) does not depend on technology, making the decisions to invest in technology separable from the decision to choose other inputs. However, we believe that a more general specification that made these decisions interdependent would yield qualitatively similar results.

For the moment, assume that technology A_{it} is held constant. Then the social planner's objective in each period is to maximize

$$(3) \quad \sum_i [\Psi y_{it} - (w_t l_{it} + r_t k_{it})]$$

where w_t is the wage rate, r_t the cost of capital, and Ψ is the implicit value to society of an extra life-year or quality-adjusted life.

The first-order conditions for capital and labor set the marginal return (in terms of the additional value of survival) equal to the cost:

$$(4) \quad \frac{\Psi\beta(1-\varphi)}{k_{it}} = r_t \text{ and } \frac{\Psi\beta\varphi}{l_{it}} = w_t$$

These imply that total costs are determined by $E_{it} = \beta\Psi$. With this specific functional form and under the strong assumptions that all hospitals are maximizing output with respect to the social planner's optimum, overall expenditures depend only on the value of life and the marginal return to medical care (through the parameter β) but not on the level of A_{it} . This is a reasonable assumption in health care, where some innovations (e.g., invasive surgical techniques) increase the returns to labor and capital intensive treatments, while others (e.g, inexpensive pharmaceutical treatments) lower the returns to labor and capital intensive treatments (e.g., Chandra and Staiger, 2007; Stukel et. al., 2005).

The key variable of interest is A_{it} , the hospital-specific productivity factor. We model this as the sum of many separate innovations, each of which may have been adopted by the physicians in the hospital to some degree. For simplicity, we assume that one new innovation becomes available each year (the model could be easily extended to allow the arrival rate of innovations to be stochastic). Letting j index the year that each innovation was first available yields:

$$(5) \quad \ln(A_{it}) = \sum_{j=1}^t \alpha_j x_{jit}$$

In equation (5), x_{jit} is the proportion of physicians who have adopted innovation j by time t , while α_j is the return to adopting innovation j . We define the frontier technology

available at time t (A_t^*) as the technology that could be achieved if a hospital had fully adopted all innovations available, i.e.:

$$(6) \quad \ln(A_t^*) = \sum_{j=1}^t \alpha_j$$

Thus, the (log) frontier increases by α_t in each year t , and the (proportional) distance that any hospital lags behind the frontier depends on the rate at which its physicians have adopted all available innovations. Thus hospitals do not generate their own innovation, but instead take the body of scientific knowledge as given.⁴

Adoption of innovations by physicians

We assume that the technology in use at each hospital is the result of search conducted by individual physicians at that hospital. Physician search might include reading medical journals, talking to or working with colleagues (“tactile” diffusion as in Keller, 2004), or attending professional meetings. Whatever the mechanism for the origins of the knowledge, individual physicians optimally choose their search intensity, based on the cost and benefits of search which vary across hospitals, and their search intensity determines the rate at which they adopt new innovations. Hospitals where physicians have low costs of search (e.g., teaching hospitals) or high benefits of search (e.g, those treating a high patient volume) will tend to search more intensively.

More specifically, we model the adoption process as a simple search model. In a given year, each physician searches for information on new innovations by taking n_{it} random draws from a known distribution (where the physician subscript is suppressed to simplify notation). Thus, n_{it} represents the search intensity of a representative physician in

⁴ We therefore ignore the possibility of learning-by-doing leading to some hospitals either innovating on their own or moving to a point outside of the frontier.

hospital i in year t . The cost of an additional draw (the marginal cost of search) is positive and varies across hospitals, and is assumed to be the same for all physicians at a hospital:

$$(7) \quad c'(n_{it}) = c_i > 0$$

On each draw, the physician learns about an existing innovation j with a small probability (λ_{jt}).⁵ Thus, the probability of *not* learning about innovation j from a single draw is $(1 - \lambda_{jt})$, while $(1 - \lambda_{jt})^n$ represents the probability of *not* learning about innovation j from n draws. Learning about a new innovation j leads to adoption and increases productivity by α_j .

We assume that λ_{jt} increases with the fraction of the national population that has already adopted (\bar{x}_{jt-1}):

$$(8) \quad \lambda_{jt} = (\pi + \mu \bar{x}_{jt-1})$$

This specification is closely related to the Bass (1969) diffusion model, a commonly used empirical specification for diffusion processes that includes logistic ($\mu = 0$) and exponential ($\pi = 0$) models as special cases. A common interpretation of the Bass model is that the first term (π) corresponds to “innovation”, and captures the rate at which individuals independently discover a new technology, while the second term ($\mu \bar{x}_{jt-1}$) corresponds to “imitation”, and captures the rate at which individuals learn from interactions with others who have already adopted the innovation. Thus, the “innovation” rate is constant over time, while the “imitation” rate grows as more physicians adopt a new innovation. For simplicity, we assume that the parameters π and μ are the same for all innovations, but one could extend the model to allow these parameters to vary across innovations.

⁵ Implicitly, $\lambda_{jt} = 0$ when $t < j$, prior to discovery of innovation j .

At the time of choosing search intensity the physician does not know the exact nature of the new innovations yet to be adopted. Thus, α_j and \bar{x}_{jt-1} are uncertain, but are drawn from known distributions.⁶ Let $f(\cdot)$ be the distribution function for \bar{x}_{jt-1} , and let $\bar{\alpha}$ be the expected value of α_j (which is the expected annual growth in productivity at the frontier). Because our model assumes that there is one new innovation per year, each physician will know the number of potential innovations remaining to be adopted ($I_{it} = t - \# \text{already adopted}$). Based on these assumptions, the expected social value of the productivity gain ($\Psi \Delta A_{it}$) from taking n_{it} draws is given by:

$$(9) \quad E(\Psi \beta \Delta \ln A_{it}) = I_{it} \bar{\alpha} \beta \Psi \int \left\{ 1 - (1 - \pi - \mu \bar{x}_{jt-1})^{n_{it}} \right\} f(\bar{x}_{jt-1}) d\bar{x}_{jt-1}$$

In other words, the expected gain in productivity from search is equal to the number of innovations that could be found times their expected impact on the (dollar) value of the productivity gain times the probability each will be discovered.

We assume that physician-specific knowledge does not decay and that physicians choose search intensity to maximize the expected discounted present value of patient survival benefits net of search cost. The total patient survival benefits in a given year are $\Psi N_i y_{it}$, where N_i is the number of patients treated at hospital i (assumed for simplicity to be constant across years). The total costs of search in each year are simply $c_i n_{it}$. Thus, letting δ be the 1-period discount factor, and assuming the physician shares the social value of saving lives, her value function is given by:

⁶ Note that the distribution of \bar{x}_{jt-1} will depend on the number of potential innovations remaining to be adopted ($I_{it} = t - \# \text{already adopted}$), and will have a lower mean when the number of remaining innovations is small (since these will tend to be more recent innovations). We have suppressed this argument from the distribution function to simplify the discussion.

$$(10a) \quad V(I_t, y_{it}) = \max_n \{ \Psi N_i y_{it} - c_i n_{it} \} + \delta E \{ V(I_{t+1}, y_{it+1}) \}$$

where the transition equations are:

$$(10b) \quad \begin{aligned} y_{it+1} &= y_{it} + \bar{\alpha} E \left\{ \left[\frac{\beta \Delta \ln A_{it}}{\partial n_{it}} \right] \right\} n_{it} \\ I_{it+1} &= I_{it} + 1 - E \{ \kappa(n_{it}) \} \end{aligned}$$

and δ is the discount rate, with $\kappa(n)$, the integral in equation (9), the expected number of new innovations found in period t . The value function for the physician reflects both the current-year benefits of additional search, and the future impact of such search, which includes the higher value of y_{it+1} (because innovations do not depreciate). However, searching harder today also has an impact on the value of search in the next period; while the $t+1^{\text{st}}$ innovation will appear on schedule (the one on the RHS of 10b), any innovations discovered in period t will reduce the number of remaining innovations to find next year.⁷

The first-order condition with respect to n is:

$$(11) \quad -c_i + \delta E \left\{ -V_I \kappa(n) + V_y \left[\bar{\alpha} E \left(\frac{\beta \Delta \ln A_{it}}{\partial n_{it}} \right) \right] \right\} = 0$$

That is, physicians trade off the marginal cost of an incremental search c_i today, against the future social benefits (in terms of survival) for the N patients (reflected in the marginal valuation function, V_y) times the marginal probability of an incremental search actually finding one of the I_{it} remaining undiscovered innovations. Offsetting this clear future benefit is the chance that, should the search uncover a new innovation this year, there will be one fewer innovation along which to search next year (the first term in the

⁷ Analytically the model is complicated by the retirement of old physicians with their acquired knowledge. We implicitly assume that the replacement physician knows at least as much as the retiring physician, for example in residency.

brackets). Note also that optimal search intensity (n_{it}) rises as the marginal cost of search (c_i) declines, and as the number of patients (N_i) rises.

The first order condition in equation (11) is stochastic, since the expected productivity gain depends on the number of potential innovations remaining to be adopted (I_{it}), which depends on the random outcomes of search in prior years. However, the marginal return to taking an additional draw is increasing in I_{it} , which in turn implies that the optimal number of draws is increasing in I_{it} . Because of this property, a physician who finds less (more) than the expected number of innovations in one year will increase (decrease) search intensity the next year. Thus, there will be a steady state search intensity (n_i^*) around which each physician will fluctuate. In other words, the model implies that there will not be convergence in output across hospitals: The productivity of physicians with high search costs or low numbers of patients will persistently lag behind the frontier, on average by an amount equal to $I_i^* \bar{\alpha}$.

Empirical Implications

Because the model yields a constant steady-state search intensity (n_i^*), the probability that a physician discovers a new innovation in any given year is written

$$(12) \quad pr(\text{adopt at } t | \text{not adopt by } t-1) = 1 - (1 - \lambda_{jt})^{n_i^*} \cong n_i^* \lambda_{jt} = n_i^* \pi + n_i^* \mu \bar{\alpha}_{jt-1}$$

(The final approximation is based on a first-order Taylor approximation.) In words, the adoption hazard depends on both the difficulty of finding information for a specific innovation, λ_{jt} , and the intensity of search, n_i^* .

One important empirical implication of equation 12 is that the hospital adoption of all innovations can be described by a one-factor model, where search intensity (n_i^*) represents the common factor linking adoption of different innovations. To see this, note that the probability that a physician adopts a given innovation by time t is given by:

$$(13) \quad pr(\text{physician } i \text{ adopt } j \text{ by time } t) = 1 - \prod_{s=j}^t (1 - \lambda_{js})^{n_i^*} \cong n_i^* \sum_{s=j}^t \lambda_{js}$$

Equation 13 uses the fact that the probability of not adopting by year t is the product of the probability of not adopting in every year up to and including year t, and again takes a first-order Taylor-series approximation. Using this approximation, the proportion of a hospital's physicians who have adopted a given innovation by time t is given by:

$$(14) \quad x_{ijt} = pr(\text{physician } i \text{ adopt } j \text{ by time } t) + \xi_{ijt} \equiv \Gamma_{jt} n_i^* + \xi_{ijt}, \text{ where } \Gamma_{jt} = \sum_{s=j}^t \lambda_{js}$$

Equation 14 is a factor model, in which the dependent variable is the proportion of physicians who have adopted a given innovation by a given year, the common factor (n_i^*) captures the intensity of search at a given hospital, and the factor loading (Γ_{jt}) reflects the length of time the innovation has been available.

A second empirical implication of our model is that the constant adoption hazard represented in equation 12 implies a partial adjustment model for the proportion of physicians adopting each technology of the form:

$$(15) \quad x_{jtt} = x_{jtt-1} + (1 - x_{jtt-1}) (n_i^* \pi + n_i^* \mu \bar{x}_{jtt-1}) + \varepsilon_{jtt} \equiv x_{jtt-1} + (1 - x_{jtt-1}) (\tilde{\pi}_i + \tilde{\mu}_i \bar{x}_{jtt-1}) + \varepsilon_{jtt}$$

The expected proportion of physicians who have adopted innovation j in time t is equal to the proportion that had adopted at t-1 plus a fraction of the physicians who have not yet adopted an existing innovation. Moreover, the adoption hazard is given by a Bass

diffusion model $(\tilde{\pi}_i + \tilde{\mu}_i \bar{x}_{jt-1})$ in which the diffusion parameters vary in proportion to each hospital's search intensity (see Young, 2006).

Summing equation (13) across all innovations (as in equation 5) and simplifying yields a partial adjustment model for technology:

$$(16) \quad \ln A_{it} = \ln A_{it-1} + \tilde{\pi}_i (\ln A_t^* - \ln A_{it-1}) + \tilde{\mu}_i \sum_{j=1}^t \bar{x}_{jt-1} (1 - x_{ijt-1}) \alpha_j + v_{it}$$

$$\text{where } v_{it} = \sum_{j=1}^t \varepsilon_{jit} \alpha_j$$

In the absence of the “imitation” effect ($\tilde{\mu}_i = 0$), equation 15 represents a partial adjustment model for technology, in which a hospital's technology adjusts part way toward the frontier each year. This partial adjustment model is commonly used in the growth literature, and was first proposed by Nelson and Phelps (1966).⁸ The presence of the imitation effect ($\tilde{\mu}_i > 0$) introduces a term that captures the additional impact of imitation on technological progress. This term is always positive, but is largest for hospitals that lag far behind the frontier, i.e. hospitals with low values of x_{ijt-1} . Thus, the imitation affect has little impact on hospitals near the frontier, while having a larger impact on the rate of technology adoption for hospitals lagging far behind the frontier.

Restating this in terms of output, and rearranging terms, yields a fairly simple specification for output:

$$(17) \quad y_{it} = (1 - \tilde{\pi}_i) y_{it-1} + \tilde{\pi}_i y_t^* + \beta \tilde{\mu}_i \sum_{j=1}^t \bar{x}_{jt-1} (1 - x_{ijt-1}) \alpha_j + \beta v_{it}$$

⁸ In their original reduced-form application, the focus was on how human capital affects the speed of adjustment. Our model derives this from an underlying model of optimal search..

Equation 17 states that output is a weighted average of last years output and output at the frontier (y_t^*), with the coefficient on lagged output expected to be lower for hospitals with more intensive search (high n_i^* , and therefore high $\tilde{\pi}_i$). Intuitively, survival rates will be more persistent in hospitals that are slow adopters of innovations, e.g. if by chance a hospital has failed to adopt innovations in the past, it will take longer to recover for a hospital that is a slow adopter. However the additional term introduced by the imitation effect will offset the persistence among very slow adopters, by increasing their rate of adoption.

Equation 17 has a number of additional implications for how the steady-state distribution of survival rates depends on the speed of adoption. It is straightforward to derive the following properties of survival in the steady state distribution:

$$(18.a) \quad E(y_{it} - y_{it-1}) = E(y_t^* - y_{t-1}^*) = \bar{\alpha}$$

$$(18.b) \quad E(y_t^* - y_{it}) = \bar{\alpha} \left(\frac{1 - \tilde{\pi}_i}{\tilde{\pi}_i} \right) - \frac{g_i}{\tilde{\pi}_i}$$

The first equation states that there is no convergence. In steady state, productivity growth is the same at all hospitals. As already discussed, this property is a direct implication of our search model, in which the steady state search intensity required physicians to lag the frontier by a constant amount. Moreover, this property has been noted in other papers using the Nelson-Phelps partial adjustment model of technology.

The second equation states that the steady-state distance that a hospital lags behind the frontier is the sum of two terms. We have already argued from the first order condition of the search model that there is a steady state search intensity (n_i^*) that is negatively related to the number of potential innovations remaining to be adopted in

steady state (I_i^*). Thus, physicians with lower search intensity will lag further behind the frontier. Equation 18.b breaks down this distance from the frontier into two distinct effects.

The first term in equation 18.b depends only on the rate of “innovative” adoption, and represents the amount that a hospital would lag behind the frontier if there were no “imitative” adoption. Since $\bar{\alpha}$ represents the average annual gain in survival at the frontier, the term $1 - \tilde{\pi}_i / \bar{\pi}_i$ represents the number of years a hospital lags behind the frontier. For example, a hospital with an “innovative” adoption hazard of 10% would lag 9 years behind the frontier, while a hospital with an “innovative” adoption hazard of 50% would lag 1 year behind the frontier.

The second term in equation 18.b captures the mitigating impact of “imitative” search, where we let g_i represent the value in steady state of the “imitative” term from equation 17. While there is no simple closed form solution for this term, it can be shown to be positive, declines to zero as the importance of “imitative” adoption ($\tilde{\mu}_i$) declines to zero, and declines with search intensity (n_i^*). Thus, this term implies that greater “imitative” adoption moves a hospital closer to the frontier in steady state, and is particularly important for hospitals with low search intensity.

Equation (17) can be simplified to yield an equation more amenable to estimation:

$$(19) \quad y_{it} = (1 - \tilde{\pi}_i - \tilde{\mu}_i \omega_i) y_{it-1} + \tilde{\pi}_i y_i^* + \tilde{\mu}_i \bar{Y}_{t-1} + u_{it}$$

$$\text{where } \omega_i \approx \omega_{it} = \frac{\sum_j \bar{x}_{jt-1} w_{ijt}}{\sum w_{ijt}}$$

is assumed constant over time for each type of hospital, and $w_{ijt} = \alpha_j x_{ijt}$. The ω_i term is a weight that reflects the correlation between the individual hospital's speed of adoption and the average, so if (for example) a hospital is a below-average adopter, the weighting factor will be larger given that each of their (old) innovations will have been adopted by other hospitals already, so that \bar{x}_{jt-1} will be approaching one, or complete adoption. (For truly sluggish hospitals who are the last to adopt, $\omega_i = 1$) If instead a hospital at the frontier derives much of its productivity from new innovations, ω will be correspondingly lower.

This simple model yields a number of strong implications. First, when use of an innovation can be observed at the patient level, we show that the rate of use of all such innovations in each hospital is described by a factor model, where the common factor is proportional to the optimal search intensity being used at each hospital. Second, our model of physician search implies a generalization of the partial adjustment model as in Nelson and Phelps (1966). Third, our model predicts that hospitals with higher adoption rates (higher search intensity) will have higher patient survival, and there will be no convergence across hospitals as growth in survival is expected to be the same at all hospitals. Finally, our model has ambiguous implications regarding how search intensity affects the persistence in patient survival rates at a given hospital. In the absence of “imitative” adoption, the model predicts that survival is less persistent in hospitals with high search intensity. But if “imitative” adoption is present, survival may also be less persistent in hospitals with low search intensity, with intermediate levels of search intensity potentially being associated with the highest levels of persistence in patient survival.

3. Data

We focus on the “production” of survival following acute myocardial infarction (AMI). There are compelling reasons to focus on heart attacks. Nearly every AMI patient who survives the initial attack is admitted to a hospital, and ambulance drivers generally take the patient to the nearest hospital, so nearly every patient who survives the initial attack is admitted to a hospital. The outcome, survival, is accurately measured and there is broad clinical agreement that survival is the most important endpoint, particularly in the elderly population. The measurement of inputs is also accurate, whether reflecting pharmaceutical treatments or demographic and health information (including the type of heart attack).

In their pioneering work, David Cutler and colleagues focused on productivity gains in AMI using similar measures of one-year survival and one-year inpatient costs although at the national level and not at the hospital level as we do here.⁹ They found dramatic improvements in health outcomes, and demonstrated that at least for AMI during this period, spending was “worth it” for Medicare patients. Thus AMI represents an important case study of technological advances in medicine, but it should be stressed that it is not representative of most health care, where productivity gains are far more modest, particularly among non-cardiac diseases.¹⁰

The primary dataset is a 20% sample of the Medicare Part A (hospital) claims data for all heart attack (AMI) patients age 65 and over in the U.S. during 1986 – 1991, and a 100% sample from 1992 through 2004, with updated information on mortality

⁹ See Cutler, et. al. (1998), Cutler and McClellan (2001), and Cutler (2004).

¹⁰ See Cutler, Rosen, and Vijan, 2006.

through 2005. The original sample comprises 3.3 million people, but in order to create a full 19-year panel of hospitals we limit the sample to 2.8 million people. The Medicare claims data includes detailed information on comorbidities (i.e., preexisting conditions), as well as the type of heart attack (e.g., inferior, anterior, and non-Q wave).¹¹ The data was pooled and checked to ensure that, at least during this period, there had been no previous AMIs in the sample.¹² We also consider Part A (inpatient) Medicare reimbursements, expressed in 2004 dollars using the GDP deflator, and risk-adjusted using the same set of covariates in a linear model.¹³

A categorical variable was created for each 5-year age bracket, by sex and race. (There are 5 ages x 2 sexes x 2 race variables in all.) The initial risk-adjustment regression is shown in Table 1 along with relevant means of the independent variables for the entire sample, for both one-year survival and one-year expenditures.

Information on the adoption of technology was measured in the Cooperative Cardiovascular Program (CCP) dataset, which involved chart reviews for over 160,000 AMI patients over age 65 during 1994/95, matched to the admitting hospital. We chose

¹¹ Comorbidities are the presence of vascular disease, pulmonary dysfunction, dementia, diabetes, liver dysfunction, renal failure, cancer, and metastatic cancer. Heart attack type is measured as anterior, inferior (denoting the location of the blockage, with anterior the most serious) and non-Q wave or subendocardial infarction. For non-Q AMI, the affected area does not extend the entire width of the heart muscle and is therefore associated with a much better clinical prognosis.

¹² Focusing on the first AMI, avoids bias resulting from mortality occurring as frailer and older AMI survivors experiencing a second MI die as a result.

¹³ Part B physician reimbursements are also available in some years, but the sample size is so small (5 percent prior to 1998, 20 percent thereafter) that these measures were not used in this analysis. A previous study focusing on the regional level (Skinner, Staiger, and Fisher, 2006) suggested that there was no substitution effect between Part A and Part B expenditures; if anything regions with higher Part A spending were more likely to experience higher Part B spending.

three measures of low-cost but effective innovations. The first, aspirin, reduces platelet aggregation and helps to limit clotting, thereby improving blood flow to the oxygen-starved tissue, and reduces mortality substantially (e.g., ISIS-2, 1988). Indeed, Heidenrich and McClellan (2001) viewed aspirin as the single most important factor in explaining why 30-day mortality rates declined during 1975-95. By 1994/95, most hospitals had adopted aspirin, with an average compliance rate of 80 percent, but with a substantial minority of hospitals with rates of 60% or below.

The second, a β blocker, is an inexpensive drug that by blocking the beta-adrenergic receptors reduces the demands on the heart. In a meta-analysis from 1985, Yusuf et. al. summarized the existing literature as “Long-term beta blockade for perhaps a year or so following discharge after an MI is now of proven value, and for many such patients mortality reductions of about 25% can be achieved.” (p. 335) By 1994/95, diffusion fell far short of ideal: average use among AMI patients was just 46 percent. Furthermore, during this time there was considerable variation in the adoption of β blockers; some hospitals had fully adopted (near 100 percent), while others were not using them at all.

Figure 2 shows this graphically for three states: Iowa, Massachusetts, and Mississippi. On the horizontal axis is the cumulative distribution of patients, ranging from 0 to 1.00, sorted by β blocker use in the hospital to which they were admitted. On the vertical axis is the fraction of patients treated at that hospital with β blockers.¹⁴

¹⁴ One can also construct this graph using the fraction of patients “ideal” for β blockers who actually receive such treatments. However, the criterion for ideal appears far too restrictive, and so we simply look at overall rates – thus the optimal rate may be below 100 percent because of patients for whom β blockers are contraindicated.

Clearly, Mississippi is lagging behind the other two states with regard to β blocker adoption; the 70th percentile of AMI patients were admitted to hospitals with a 33 percent rate of β blocker use, which is the use rate at the hospital to which the 1st percentile of Massachusetts AMI patients were admitted. But it is still noteworthy that there are hospitals in Mississippi with rates of β blocker use that were above those in Massachusetts and Iowa. The use of β Blockers has since risen substantially; in 2000/2001 the median state was at 68 percent compliance (with Iowa one of the best), and currently it is rare to find hospitals using β blockers for fewer than 90 percent of AMI patients.¹⁵

One could interpret these patterns as reflecting demand; patients in Massachusetts ask for and get β blockers. But it seems unlikely that this could explain the patterns we observe; these are elderly heart attack patients who are in quite serious condition and unlikely to be well schooled in the latest methods of AMI treatment. More to the point, hospitalized patients should not *have* to ask their physicians for β blockers, aspirin, or reperfusion.

The third measure is reperfusion within 12 hours of the AMI. The objective is to get blood to the oxygen-starved heart muscle quickly, and this can be effected either by using thrombolytics, drugs which help break down the clots blocking the blood, or angioplasty, in which a “balloon” is threaded through a vein into the blocked artery and expanded, thus restoring blood flow (Since 1995, cardiologists have increasingly adopted stents, cylindrical wire meshes, to maintain blood flow.) The two treatments are

¹⁵ See www.hospitalcompare.hhs.gov for a complete listing of reporting U.S. hospitals and their measures of β blocker use. The reporting is not complete for all hospitals, leading to the possibility of upward bias.

substitutes because thrombolytics reduce the patient's ability to clot. Randomized trials have shown both to be highly effective, but with most studies showing slightly larger benefits for angioplasty. By 1994/95, many larger hospitals had catheterization laboratories, but thrombolytics were a viable option for all hospitals.¹⁶

4. Model Estimation and Results

We begin with summary statistics on productivity in the treatment of AMI. Figure 1 shows risk-adjusted one-year survival and one-year expenditures by year. Survival rose rapidly during the late 1980s and early 1990s (the period of analysis in Cutler et. al., 1998), but since then has flattened out, particularly in the late 1990s, before assuming a more modest upward trend in the 2000s. What can explain this pattern of sharply diminishing returns to technology after the mid-1990s? One potential explanation comes from Heidenrich and McClellan (2001), who identified aspirin as the primary engine of productivity growth, followed by treatments such as β blockers, thrombolytics, and primary angioplasty. By 1995, with average rates of use of aspirin at 80 percent, the extent of further productivity gain was limited. But continued growth in other treatments such as β blockers, thrombolytics, and PTCA should have resulted in at least some additional benefits, and why these gains were not observed is something of a mystery.¹⁷

¹⁶ We consider only angioplasty within 12 hours of the AMI, when there is still a chance of recovering heart muscle. The vast majority of angioplasties are performed for AMI patients after 12 hours, or for people with cardiac ischemia. For these patients, there are no well-established survival benefits, although there may be modest improvements in functioning (e.g., Boden, et. al., 2007).

¹⁷ See also Ash, et. al. (2003) who find a similar flattening in mortality. Sample selection during the era of growth in Medicare managed care is another possibility, but Skinner et. al. (2006) argues that this trend was unlikely to explain the plateau.

As shown in Figure 1, there has also been a dramatic increase in expenditures during the late 1980s and early 1990s, and while the 1997 Balanced Budget Act legislation flattened Part A reimbursements, expenditures have since resumed an upward trend. It is not difficult to see a close correlation between the two time-series, and we consider this correlation in more detail below at the hospital level after estimation of the factor model.

Estimating the factor model

Consider first the hospital-level data on adoption rates of the three recent innovations to estimate the factor model in Equation (14). The factor model was estimated using the proportion of patients receiving each treatment for each hospital in 1994/95, and assuming a single common factor. Predictions of each hospital's factor were constructed using standard methods. These predictions are simply a weighted average of the three dependent variables, where the weights are derived from the parameters of the factor model. Factor analysis normalizes the underlying factor to have a mean of zero and variance of one, so the units of the estimated factor have no particular interpretation.

Table 2a presents the correlation coefficients among the three variables (aspirin, β blockers, and reperfusion) and the common factor. The correlation of each input with the common factor ranges from 0.87 for β Blockers to 0.30 for reperfusion, demonstrating that hospitals that adopt one innovation early are also more far more likely to adopt other innovations. In Table 2b, we show that the quintiles based on this factor show clear differences in the use of β blockers (from 64 percent in the highest adopting quintile to 27 percent in the lowest) and aspirin (90 percent to 62 percent), with more modest

differences in reperfusion (21 percent to 14 percent).¹⁸ Consistent with our model, hospitals in the quintiles with quicker adoption also have higher patient volume, and are more likely to be major teaching hospitals.

There are also clear differences in risk-adjusted survival for each of the quintiles of adoption. Figure 3 shows survival rates for each of the five quintiles by year. On average, the gap in survival between the slowest and most rapid adopters was more than 3 percentage points, with the difference widening to 3.5 percent by 2004.

Figure 4a displays Medicare reimbursements again by quintile of adoption. There are modest differences in expenditures, with Quintile 1, the most rapidly adopting hospitals, consistently higher. However, this difference is based primarily on higher reimbursement rates rather than more inputs *per se*. The Medicare reimbursement system is based on diagnostic related groups (DRGs) where each procedure is assigned a common resource “weight”, with payments varying across hospitals because of cost adjustments, the number of residents, and supplemental payments to compensate for serving low-income patients. Figure 4b shows expenditures by quintile using a normalized “price” per DRG weight based on the national average. As is clear, there are no differences in resource inputs across hospital quintiles.¹⁹

Convergence

Equation 17a states that survival rates should grow at the same rate for all hospitals. Figure 3 demonstrated a lack of convergence in survival by quintile. We test

¹⁸ These averages are for all patients and not for “ideal” patients. In practice it is difficult to identify ideal patients. While nearly all patients should receive β blockers and aspirin, the optimal rate for revascularization is below 100 percent.

¹⁹ Also see Skinner, Staiger, and Fisher (2006) and Fisher et. al. (2003a,b).

this further in Figure 5 which shows the average hospital-level variance in risk-adjusted survival for each year, adjusted for differences in the sample size of each hospital.²⁰

Figure 5 displays the standard deviation of this distribution, which ranges from 3 to 5 percentage points, and does not suggest convergence over the time period. If anything there is a marked divergence in the 2000s.

Estimating a production function

While the log-linear specification of the production function has strong implications for the constancy of expenditures over time from Equation (4), holding Ψ constant, this does not preclude us from estimating Equation (3) with a measure of factor inputs on the right-hand side of the equation. While we cannot distinguish exactly between capital and labor, we can think of “inpatient” and “outpatient” inputs to health, where our measure of factor inputs for inpatient care, whether Medicare reimbursements or DRG weights, is accurate and can be compared both across hospitals and over time.

Table 3 presents the coefficient estimates from a series of regressions involving a measure of factor inputs and technology adoption on the RHS, and survival on the LHS, of the estimating equation. Depending on the specification of the model, we may include year effects, hospital effects, or adoption quintiles in the regression. All regressions are weighted by the number of AMI patients in each year-hospital measure (with a minimum of 5 patients per hospital).

²⁰ This is done by subtracting an estimate of the “noise” component of the variance, equal to σ_u^2/N_h where σ_u^2 is the variance of the hospital-level risk-adjustment equation and N_h is the measured volume of AMI patients at hospital h . Recall that prior to 1992, the sample size is just 20% rather than 100%. Thus the relative smoothness of the transition between 1991 and 1992 is at least suggestive that the adjustment for “noise” is doing an adequate job.

In the first row of Table 3, we replicate a regression in the spirit of the Cutler studies (e.g., Cutler et. al., 1998) that compared changes in survival rates and Medicare Part A expenditures without year-specific effects. In this regression at the hospital level, the coefficient on the log of costs is 0.0227 ($t = 12.2$) which translates to an implicit cost-effectiveness ratio of \$196,000 per life year, which is not a particularly favorable cost-effectiveness ratio.²¹ Strictly speaking, Equation (3) implies that quantities should matter more than expenditures, and so we re-estimated the model using log DRG weights instead.²² For the period prior to 1995 considered by Cutler et. al., factor inputs are estimated to be highly productive, with a cost-effectiveness ratio of \$42,000 per life year. Since 1995, however, there is no association between factor inputs and survival, so the cost-effectiveness ratio is not defined.

There is considerable variability in the magnitude of the factor input effects depending on whether hospital effects and quintiles of adoption are used, as shown in Rows 4-7 of Table 2. There is also strong evidence that the estimate of β varies across technology adoption quintiles. Figure 6 shows predicted outcomes for the quickest adopting hospitals (Quintile 1), the middle group, and the slowest adopting hospitals (Quintile 5) using coefficients from a model with log (DRG) and year dummy variables, stratified by quintile (Rows 8-10 in Table 3). At every level of expenditures, hospitals in

²¹ The cost-effectiveness ratio is calculated by assuming that every additional patient who lives an extra year will attain 5.25 life years, the average expected lifespan of heart attack patients based on Cutler et. al., 1998. Generally cost-effectiveness ratios below \$50,000 are viewed favorably, but inflation has lead many to view \$100,000 as a more reasonable cut-point.

²² During this period, reimbursement mechanisms were adjusted to benefit some hospitals over others, so that cost increases were in part the result of political factors.

the highest adoption group dominate those in the lowest adopting group; even spending \$50,000 per case in the low-adoption group would still result in worse outcomes compared to spending \$10,000 per case in the high-adoption group. The results are less dramatic using regression models with hospital-specific effects (Rows 11-13); these capture only the within-hospital effects. Finally, the last column (Row 14) shows a poor incremental value for money spent in the top quintile when we use log of costs rather than log of DRGs (cost-effectiveness ratio of \$262,000)..

Estimating the time-series model

We next turn to the estimation of the model in Equation (19). We first consider just the Nelson-Phelps frontier model without any imitation parameter, estimated in a nonlinear model without a constant term by quintile. We experimented with a number of approaches to defining the “frontier” of heart attack treatments, including the US News and World Report “40 Best” cardiac hospitals. (While these hospitals were in fact ahead of other hospitals in the 1980s, by 2004 they resembled more closely the average hospital.) We therefore used Quintile 1, the most rapid adopting hospitals, as the frontier, and test whether there are any patterns with regard to the gravitational force of the frontier (versus the average) for Quintiles 2-5. Column 1 in Table 4 begins with the simplest Nelson-Phelps frontier approach, where survival this year is a weighted average of survival at the hospital last year and the frontier. We estimate the model where last year’s survival is instrumented by the second lag in survival, and all estimates are weighted by the number of patients in each hospital. (To reduce measurement issues we further restrict the sample to hospitals/years with at least 25 patients.) The non-linear estimates of π suggest an inverse U-shape (rather than a U-shape as suggested by the

model); 0.10 for the bottom quintile, 0.13 for quintile 2, but the maximum attained at quintile 3 (0.214). That the monotonic association between π and adoption is not observed suggests that we should at least test for imitation effects.

The remaining columns show results that allow for values of π and μ to differ across hospitals.²³ (Our theory assumes that the two should be a constant proportion of one another, but we relax that assumption in the regression analysis). Columns 2-4 present alternative estimates of this model; these differ either because of aggregation (Column 2 uses OLS with the quintile-specific aggregated survival rates) or because of the introduction or exclusion of a constant term (Columns 3 and 4). The estimates are not stable and often outside the admissible range (e.g., μ is negative in Columns 3 and 4) and so no definitive conclusions can be reached. Still, the patterns across quintiles is at least suggestive that the rapidly innovating hospitals are drawn most closely to the frontier, while lagging hospitals are relatively more influenced by imitative behavior.

5. Conclusion

In this paper, we have developed a search model of hospital productivity with a particular focus on peering inside the black box of technological innovation. We found that varying rates of adoption for low-cost but highly effective treatments explained a large fraction of the persistent differences in risk-adjusted survival during the period 1986-2004. The hospital quintile with the most rapid propensity to adopt these new innovations (or the “frontier”) experienced survival rates 3.3 percentage points above the lowest quintile hospitals, or nearly one-third the entire improvement in survival since

²³ We focus on π and μ , the free parameter ω means that there are no restrictions on the lagged survival coefficient as there is for the Nelson-Phelps model where there is just one parameter and two regression coefficients.

1986. While we focused on just three innovations at a point in time, aspirin, β blockers, and reperfusion in 1994/95, we view the results, and the non-convergence of the quintile outcomes, as supportive of the view that these hospitals have continued to innovate since then.²⁴

These results have implications for both health policy and for productivity more generally. With regard to health policy, there is an ongoing debate about whether we're getting our money's worth from the U.S. health care system. Some researchers have pointed to the dramatic improvements in life expectancy, particularly with respect to cardiac diseases, and concluded that while the U.S. health care system is expensive, the expenditures are worth it (e.g., Cutler, 2004; Murphy and Topel, 2003). By contrast, others have estimated that the U.S. health care system displays efficiency characteristics that rank below those in Albania (Evans, 2001). Fisher et al (2003a,b) for example has found that patients in regions with greater degrees of health care intensity are not sicker at baseline, but do subsequently experience slightly *worse* outcomes, poorer access to care, and less satisfaction.

These two views are entirely consistent in an environment where there are regional or hospital differences in the productivity of health care. Hospitals with less ability to adopt new innovations lag behind consistently in the quality of care, and may compensate by using expensive treatments to compensate for the β blocker not taken. On the other hand, all hospitals, high and low quality, improve at roughly the same rate as innovations slowly percolate back to the hospitals that are slowest to adopt. More

²⁴ Preliminary results suggest a strong positive correlation between β blocker use in 1994/95 and the adoption of drug-eluting stents in 2003.

generally, productive efficiency will not depend simply on whether regions adopt quickly, but *which* treatments are adopted – are they low-cost effective treatments such as β blockers and aspirin for heart attacks, or are they well-remunerated procedures with unproven effectiveness such as instrumentation for spinal fusion (Brox, et. al., 2003)?

Note also that our model is not a “flat of the curve” story *per se*. Variations at a point in time across regions may show no association between expenditures and outcomes, but this finding is perfectly consistent with a positive upward sloping production curve (as we find), but where differences across regions are dominated by differential rates of technology adoption (Skinner, Staiger, and Fisher, 2006).

Why are physicians so slow to adopt the low cost technologies? There are a variety of economic models where maximizing behavior corresponds to slow adoption for some people. For example, rational agents may wait for the price of the innovation to decline (e.g., flat-screen TVs), or they may have developed expertise in the older technology (Jovanovic and Nyarko, 1996). Alternatively, heterogeneity in production functions may lead to profit-maximizing differences in rates of diffusion (e.g., Griliches, 1957), or the presence of liquidity constraints may restrict diffusion (Suri, 2006). Finally, there may be differences in education across workers which affect their propensity either to adopt (Nelson and Phelps, 1966) or new technology may be most complementary with skilled workers (Caselli and Coleman, 2006). Unfortunately, none of these models provides a good explanation of the non-adoption of inexpensive β blockers, aspirin, and thrombolytics by highly educated physicians. Because prices do not play a large role

here, we instead look to informational or search barriers as an explanation for why physicians don't adopt.²⁵

Without solving our model explicitly, it is useful to “back out” what must be the barrier to adopting. Assume that a life-year is worth \$50,000, that the average physician has 20 patients per year, the “default” likelihood of an adoption in a given year is 20% (so the expected number of years until adoption if not adopted this year is 5), the discount rate δ is .95 and using the innovation yields an increase of 0.08 additional life years per patient. A simple calculation suggests that the marginal equilibrium cost to the physician of raising the chance of adopting this new innovation by just *1 percent* (i.e., raising the chance of finding the new innovation from 20 to 21 percent over the space of a year) would need to be \$3,360 in order to satisfy first-order conditions. This seems implausibly large. Perhaps our assumed value per life-year is too high (perhaps because of a principal-agent problem in which physicians are not acting for “society”) or the assumed discount rate is too high, where hyperbolic or procrastination models would suggest much lower values of δ . On the other hand, this slow diffusion may also reflect extreme loss aversion where concerns about causing harm require the presence of another physician in the hospital to assist in learning about the new treatments. Still, the non-use of aspirin is difficult to explain even in models of tactile diffusion (Keller, 2004).

We are certainly not the first to point out that variations in technology appear to be more important in explaining output disparities than variations in factor inputs. In 1966, Harvey Leibenstein notes that:

²⁵ The distinction between “inefficient” barriers to adoption, and the slow, but optimal, adoption of technology for a variety of reasons, was made by Coleman (2004).

Frederick Harbison reports visiting two petroleum refineries in Egypt less than one-half mile apart. “The labor productivity of one had been nearly double that in the other for many years. But recently, under completely new management, the inefficient refinery was beginning to make quite spectacular improvements in efficiency with the same labor force” [p. 373]. We may inquire why the management was changed only recently whereas the difference in labor productivity existed for many years. It is quite possible that had the motivation existed in sufficient strength, this change could have taken place earlier.

The fundamental point of the paper is that two different firms with seemingly similar factor inputs experienced vastly different outputs; Leibenstein labeled the more efficient refinery “X-efficient.” In hindsight, perhaps his emphasis on “motivation” was unfortunate; Stigler (1976) noted that if only the Romans were sufficiently motivated, they too could have discovered America. We do not speculate about motivation in this paper, but instead focus on precisely the mechanisms by which some hospitals seems to attain much better productivity than others.

Finally, one must be cautious about drawing too many parallels between the highly distorted market for health care and other sectors of the economy. It is likely that if patients both knew about technology adoption and responded to published and reliable information about hospital quality, that N , the number of patients per physician, would respond rapidly to better technological adoption and punish laggards. Still, when there is slack in markets for health care quality, or refined petroleum in Egypt, remarkably large inefficiencies could be generated by seemingly unimportant informational barriers.

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		One-year Survival	One-Year Expenditures
	Mean	Coefficient	Coefficient
Vascular Disease	0.070	-0.029 (0.001)	1642 (56)
Pulmonary Conditions	0.189	-0.082 (0.001)	1339 (37)
Dementia	0.029	-0.137 (0.002)	-4949 (84)
Diabetes	0.247	-0.041 (0.001)	1915 (33)
Liver Disease	0.003	-0.245 (0.005)	-2102 (269)
Renal Disease	0.023	-0.284 (0.002)	1155 (94)
Cancer	0.043	-0.165 (0.001)	-2733 (70)
Anterior Infarct	0.163	0.045 (0.001)	1509 (46)
Inferior Infarct	0.178	0.113 (0.001)	719 (45)
Subendocardial Infarct (non-Q)	0.426	-0.132 (0.001)	2491 (41)
Constant (for non- black male age 65-69		0.722 (0.003)	24308 (166)
Age-Sex-Race-Year Categorical Variables		Yes	Yes
Sample Size	2,808,171	2,808,171	2,808,170
Note: Other type of AMI is the excluded category. Standard error of estimate in parentheses.			

Table 1: Means and Regression Estimates: Basic Risk Adjustment Linear Model

	Common Factor	Aspirin	β Blocker	Reperfusion
Common Factor				
Aspirin	0.871*			
β Blocker	0.792*	0.429*		
12 Hour Reperfusion	0.300*	0.189**	0.031	
Notes: Analysis performed at the hospital level (N = 2765) in the lower left-hand triangle, based on data from the Cooperative Cardiovascular Project (CCP), 1994/95, with a sample of 151,181 AMI patients. * denotes $p < 0.001$, ** $p < 0.01$.				

Table 2a: Characteristics of Factor Model of Adoption: Covariance Structure

	Quintile 1 (Quickest)	Quintile 2	Quintile 3	Quintile 4	Quintile 5 (Slowest)	Overall
Aspirin	0.90	0.85	0.80	0.73	0.62	0.80
β Blocker	0.64	0.51	0.44	0.38	0.27	0.47
Reperfusion within 12 hours	0.21	0.20	0.18	0.17	0.14	0.18
Average hospital volume*	95	100	94	82	59	89
Major teaching hospital	0.43	0.29	0.21	0.11	0.05	0.24
See notes above in Table 2a. *Volume for Medicare patients only. Weighted by number of patients in each group						

Table 2b: Characteristics of Factor Model of Adoption: Association with Characteristics of the Hospital

Regression	Input [Quintile if Stratified]	Period of Analysis	Year Effects	Hospita l Effects	Adj. for Diffusion Quintile	Coefficient (t-statistic)	Cost- Effectiveness (per Life Year)
1	Log(Costs)	86-04	No	No	No	0.0227 (12.2)	\$196,000
2	Log(DRG)	86-04	No	No	No	0.0758 (28.2)	\$59,000
3	Log(DRG)	86-94	No	No	No	0.1052 (30.3)	\$42,000
4	Log(DRG)	95-04	No	No	No	-0.005 (1.0)	[not defined]
5	Log(DRG)	86-04	Yes	No	Yes	0.0638 (16.0)	\$70,000
6	Log(DRG)	86-04	Yes	Yes	No	0.0518 (18.8)	\$86,000
7	Log(Cost)	86-04	Yes	Yes	No	0.0239 (11.1)	\$186,000
8	Log(DRG) [Quintile 1]	86-04	Yes	No	Yes	0.0409 (8.8)	\$109,000
9	Log(DRG) [Quintile 3]	86-04	Yes	No	Yes	0.0160 (3.0)	\$278,000
10	Log(DRG) [Quintile 5]	86-04	Yes	No	Yes	0.0033 (0.6)	\$1.3 Mill.
11	Log(DRG) [Quintile 1]	86-04	Yes	Yes	Yes	0.0649 (12.9)	\$69,000
12	Log(DRG) [Quintile 3]	86-04	Yes	Yes	Yes	0.0441 (7.3)	\$101,000
13	Log(DRG) [Quintile 5]	86-04	Yes	Yes	Yes	0.0391 (6.6)	\$114,000
14	Log(Cost) [Quintile 5]	86-04	Yes	Yes	Yes	0.0170 (3.5)	\$262,000

Notes: N = 49932, all regression weighted by sample size, limited to hospital/year observations with at least 5 observations per hospital.

Table 3: Regression Estimates of Survival and Factor Inputs

	Nonlinear (Nelson-Phelps)	OLS (Constant)	IV (Constant)	IV (No Constant)
<i>Innovation Parameter (π)</i>				
Rapid Diffusion (Q1)	--	--	--	--
Quintile 2	0.135 (3.0)	0.638 (4.5)	0.508 (3.1)	0.649 (4.3)
Quintile 3	0.214 (5.9)	0.288 (1.4)	0.668 (4.3)	0.770 (5.3)
Quintile 4	0.124 (4.3)	-0.023 (0.1)	0.170 (1.0)	0.278 (1.9)
Slow Diffusion (Q5)	0.099 (4.2)	0.250 (2.3)	0.302 (1.8)	0.367 (2.4)
<i>Imitation Parameter (μ)</i>				
Rapid Diffusion (Q1)	--	--	--	--
Quintile 2		0.115 (0.3)	-0.697 (4.3)	-0.672 (4.2)
Quintile 3		0.798 (1.3)	-0.716 (4.3)	-0.687 (4.2)
Quintile 4		0.741 (2.9)	-0.205 (1.3)	-0.181 (1.1)
Slow Diffusion (Q5)		0.643 (2.2)	-0.291 (1.7)	-0.270 (1.6)
	5266 [Hospital by Year]	76 [Quintile by year]	5266 [Hospital by Year]	5266 [Hospital by Year]
Notes: Hospitals-by-year observations included only if current, lagged, and lagged twice observations included at least 25 AMI patients in each hospital.				

Table 4: Parameter Estimates

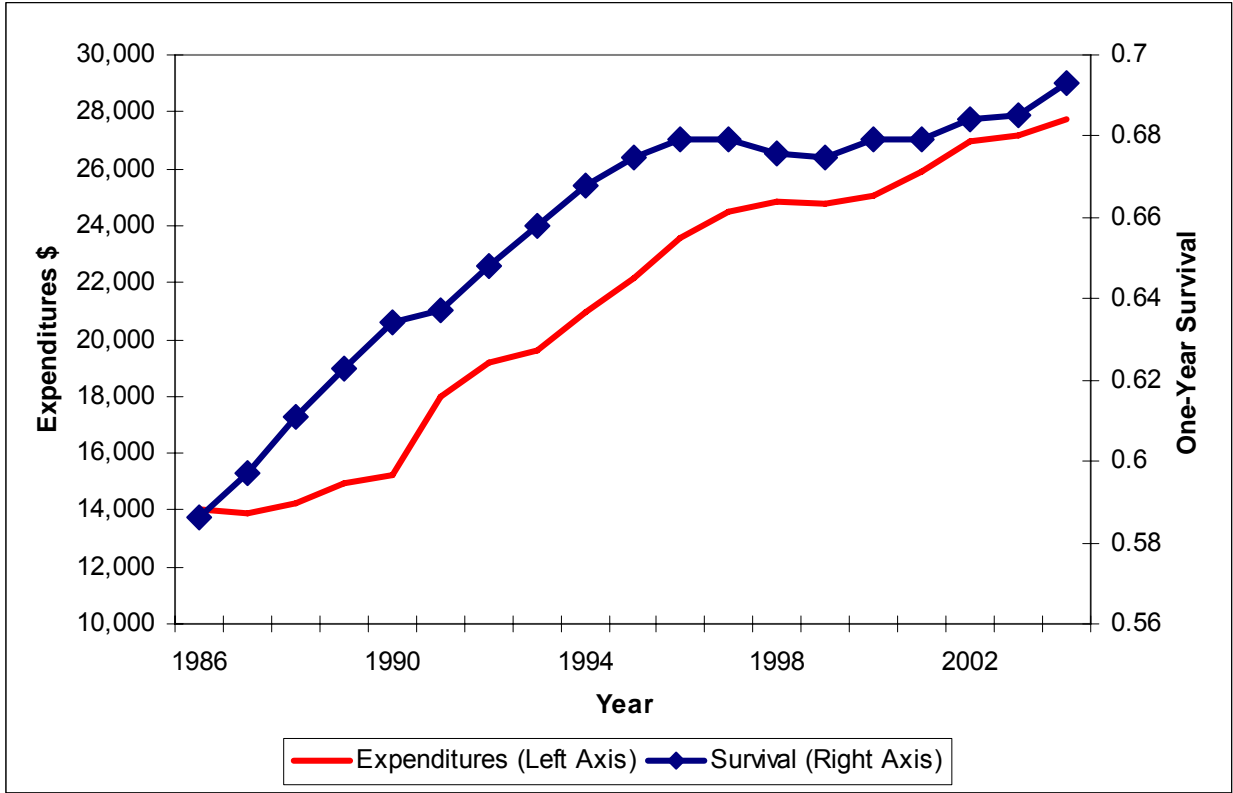


Figure 1: One-Year Risk-Adjusted Survival Rate and One-Year Inpatient (Part A) Hospital Expenditures Following AMI (2004\$)

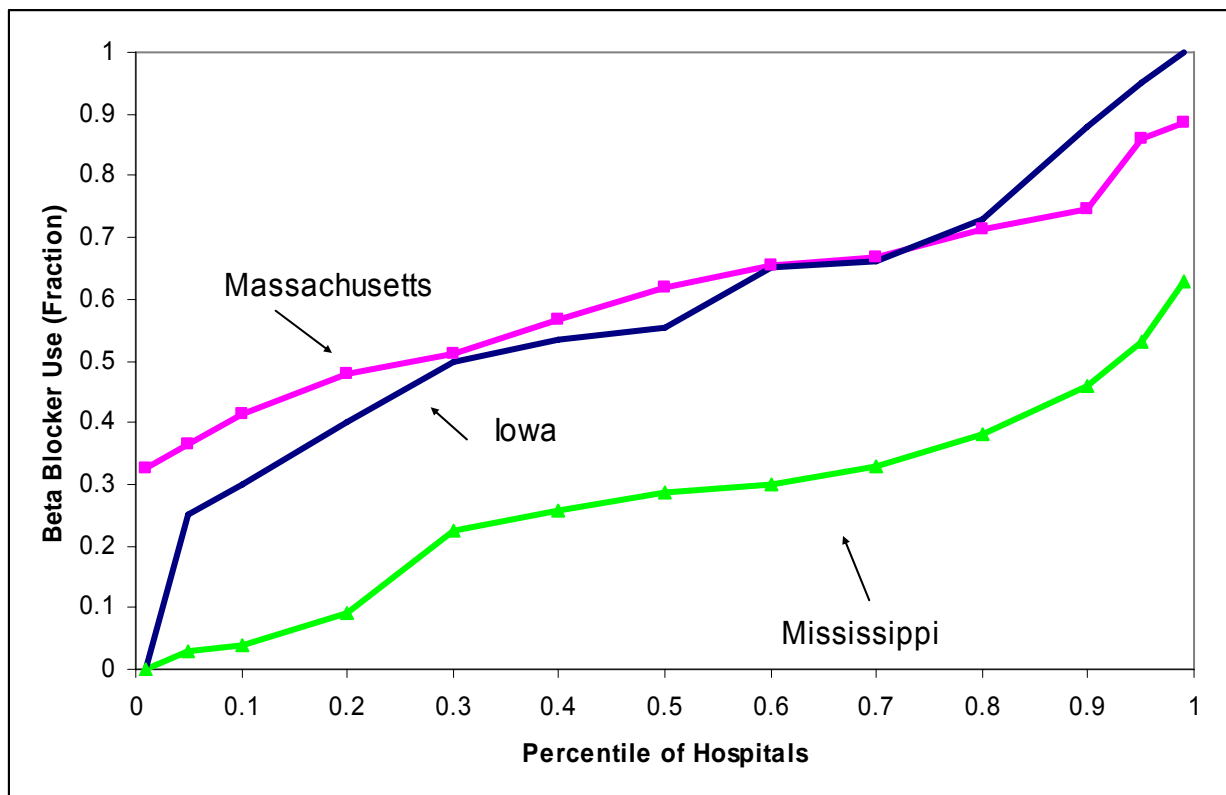


Figure 2: β Blocker Adoption in Massachusetts, Iowa, and Mississippi, 1994/95

Source: Cooperative Cardiovascular Project, 1994/95

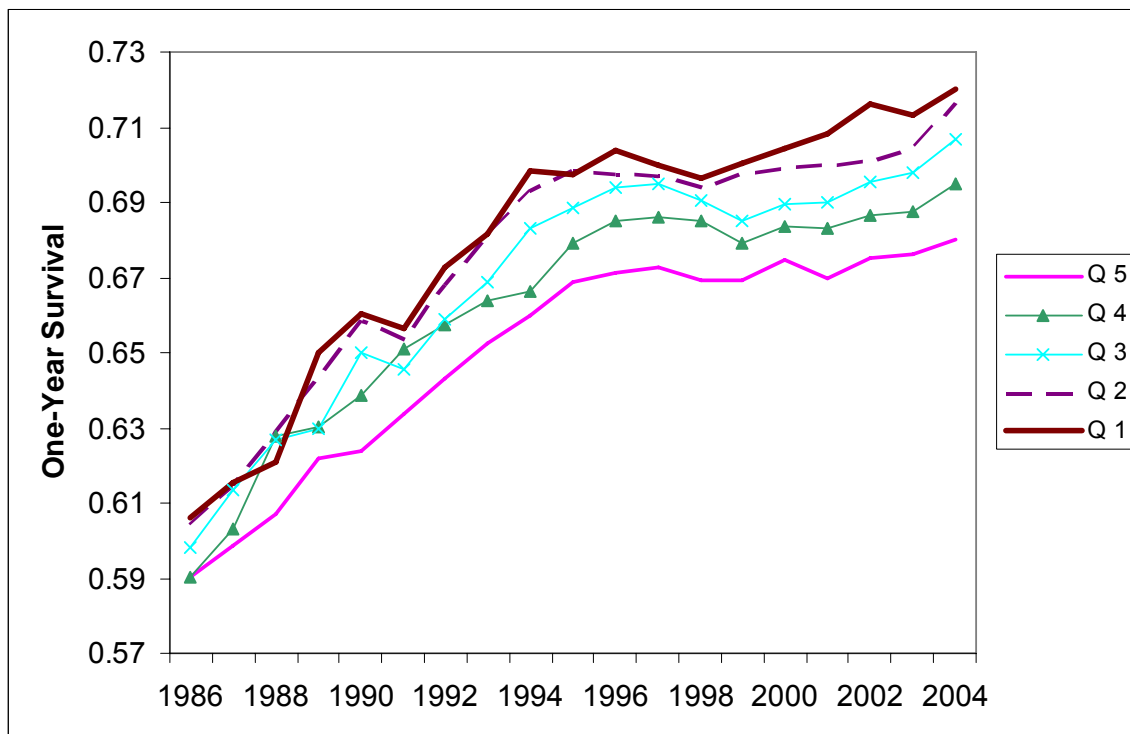


Figure 3: Survival Rates by Year and Quintile of the Propensity to Adopt, 1986-2004

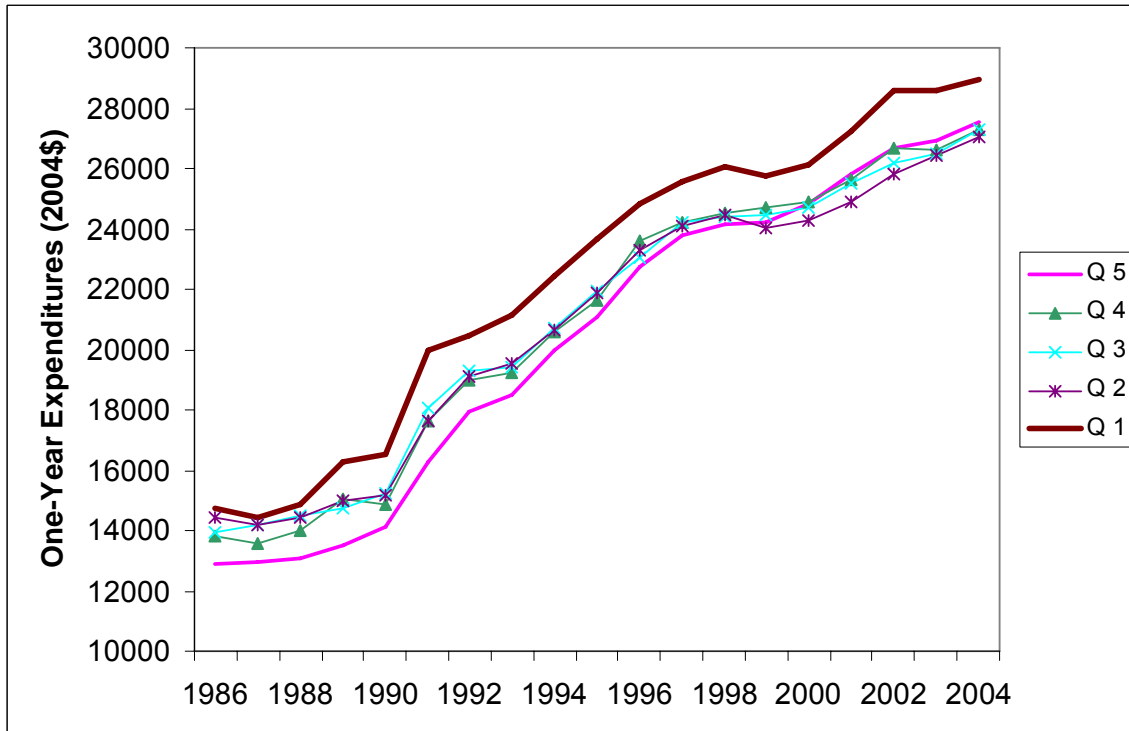


Figure 4a: Medicare Reimbursement by Year and Quintile of the Propensity to Adopt

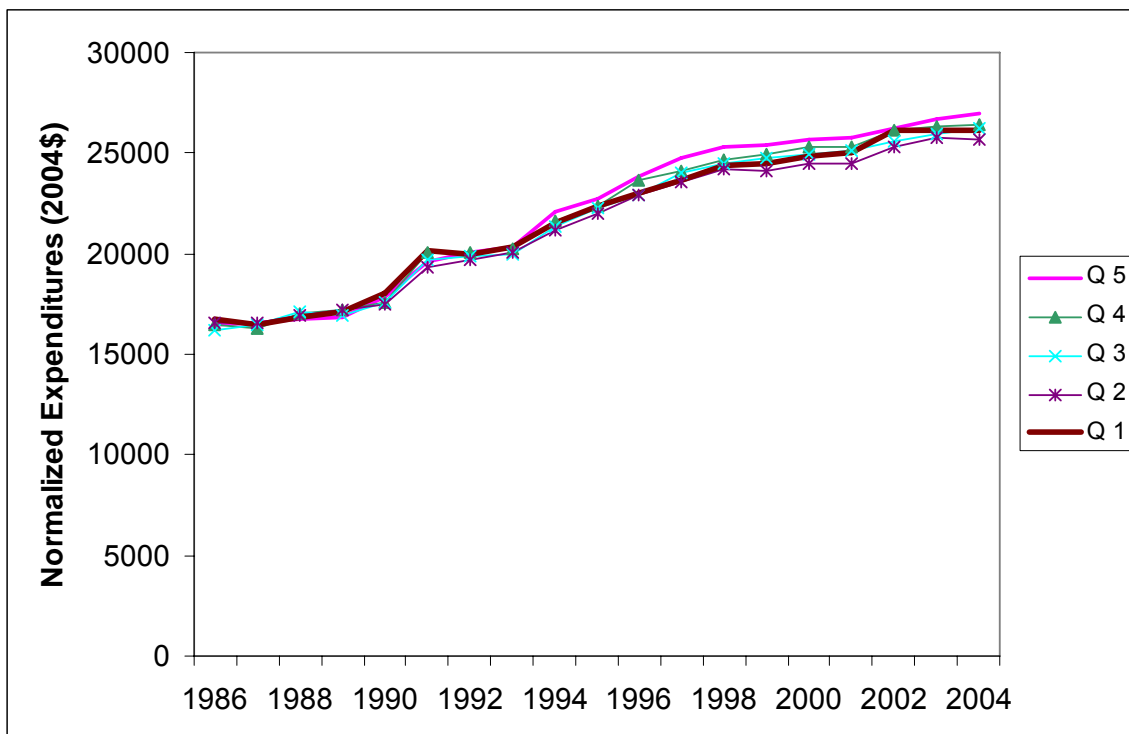


Figure 4b: Normalized Medicare Reimbursements (DRG Weights Multiplied by Common Reimbursement Rate)

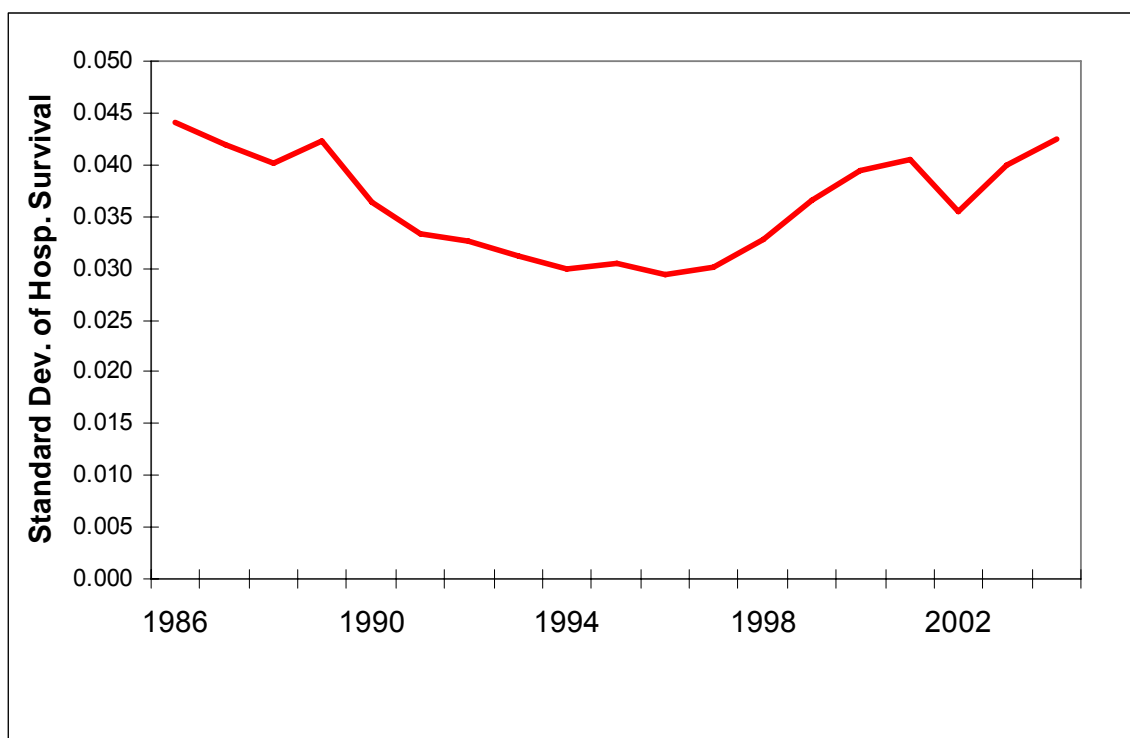


Figure 5: Standard Deviation of Hospital Risk-Adjusted Survival with Corrections for Differences in Hospital Sample Sizes

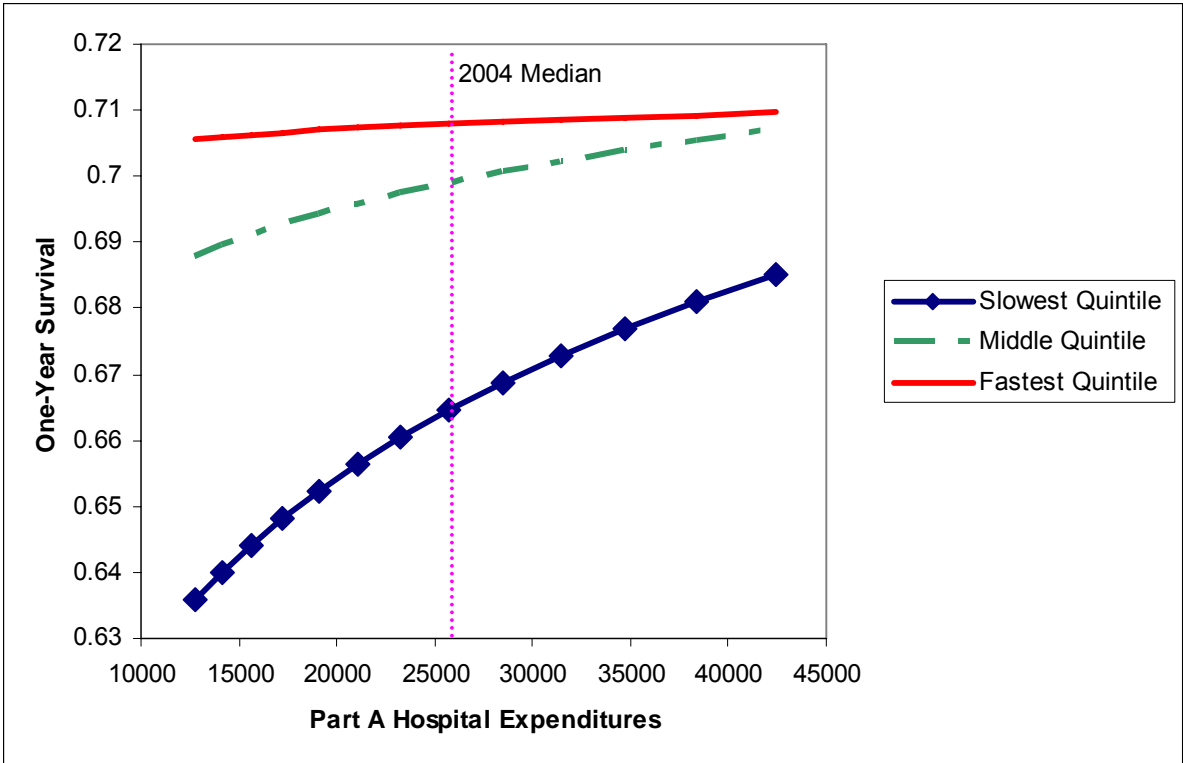


Figure 6: Implicit Log Production Functions for Quintiles 1 (Fastest) 3 (Middle) and 5 (Slowest) Hospitals, 2004

Note: Estimates based on regression analysis reported in Table 3.