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Abstract

This paper studies patient volume and the severity of case mix as they relate to physicians' human capital accumulation and pace of technology adoption by exploring a quality signaling mechanism through which physicians build peer reputation. We show that volume building leads physicians to actively manage case mix and find that successful surgeries (particularly for difficult cases) raise future volume, whereas failed surgeries (particularly for easy cases) deplete it. Surgeons with a high patient census and a low-severity case mix adopt the new technology more rapidly. These findings highlight the role of peer reputation for growing practice size and the timing of technology adoption.

Disciplines

Health Services Research | Other Medicine and Health Sciences

The Formation of Peer Reputation among Physicians and Its Effect on Technology Adoption

Amol Navathe and Guy David
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This paper studies patient volume and the severity of case mix as they relate to physicians' human capital accumulation and pace of technology adoption by exploring a quality signaling mechanism through which physicians build peer reputation. We show that volume building leads physicians to actively manage case mix and find that successful surgeries (particularly for difficult cases) raise future volume, whereas failed surgeries (particularly for easy cases) deplete it. Surgeons with a high patient census and a low-severity case mix adopt the new technology more rapidly. These findings highlight the role of peer reputation for growing practice size and the timing of technology adoption.

I. Introduction

Physicians play a pivotal role in decisions that affect almost every aspect of health care, and as coordinators of care, their influence spreads across most segments of the health system. The welfare implications of health care delivery are centered on patient well-being; patients rely on physicians for advice and treatment, which makes physicians interesting and challenging economic agents to study. As physicians gain expertise through medical education and training, as well as from their experience, continued education, and peers, it is not surprising that asymmetric information between physicians and their patients has received ample attention in the literature (McGuire 2000). While asymmetric information is at the heart of patient-physician relations, it plays a different role in physician-physician relations. Peer relations may influence the accumulation of human capital more than patient-physician relations. In particular, peer relations may influence the professional success and livelihood of physicians. The impact of peer relations on welfare, while indirect, may be significant.

In general, peer relations influence decisions made by physicians re-

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garding patient flow, continuity of care, diagnosis modality, and treatment options. One of the key decisions made by physicians is their choice of technology in diagnosis and treatment (Escarce et al. 1995). New medical technologies are frequently introduced by pharmaceutical companies and medical device manufacturers, sometimes with involvement of physicians. However, when a technology is introduced, the timing of its adoption and the extent to which it is used may vary across those who utilize it (Freiman 1985; Greer 1988; Escarce et al. 1995; Escarce 1996; Hirth, Fendrick, and Chernew 1996; Burt and Sisk 2005; Gans et al. 2005). It has been argued that the heterogeneity in the timing and extent of adoption may be linked to peer relations and that the nature of professional ties may lead to either underutilization or overutilization of new technologies from a welfare perspective (Escarce 1996). For example, a delay in adoption of a technology that increases quality of life and patient survival would lower social welfare.

To the extent that physicians' utility encompasses more than their patients' utility, peer relations may be an important vehicle for achieving individual lifetime objectives. Specifically, physicians may take actions to establish, maintain, and enhance their reputation among colleagues when peer reputation affects their utility directly or indirectly (e.g., practice size). Similarly to Diamond (1989), we define peer reputation as a perceived quality stock by peers.¹ This stock, though correlated, is different from the stock of human capital since it can be augmented or depreciated as past patient outcomes are translated into signals for physician quality among peers. Physician quality is defined as the likelihood that a physician will produce a positive outcome on any given case (higher likelihood means higher quality). Physicians possess strong incentives to manage the perceptions of colleagues about their own quality because of the referral mechanism through which they receive patients. Naturally, the physician's years in practice, board certification, and training may serve as a quality signal for peers as well. Referring physicians are charged with matching their patients with the most appropriate physician for a particular treatment and, given the repeated nature of peer interactions, may retain an incentive to track performance of peer physicians and surgeons over time (Gurmankin et al. 2002; Schwartz, Woloshin, and Birkmeyer 2005).²

Because peer reputation is itself unobservable in the data, study of its formation as well as its effect on optimal timing of adoption necessitates a theoretical construct to provide a link to empirical analysis.

¹ Diamond (1989) describes reputation as "arising from learning over time from observed behavior about some exogenous characteristics of agents. Reputation effects on decisions arise when an agent adjusts his or her behavior to influence data others use in learning about him" (829).

² Physician referral recommendations have been shown to influence patient decisions, and patients indicate physician referral as a key factor in determining the best surgeon for their particular case (Schwartz et al. 2005).

The literature on quality signaling for experience and credence goods has largely focused on the role of contractual commitment mechanisms that enhance producer liability as a signal rather than the informational content of outcomes (Spence 1977; Wilson 1980; Klein and Leffler 1981; Shapiro 1983; Akerlof 2000).³ Klein and Leffler (1981) point to the role of prices for signaling product quality. Shapiro (1983) extends the idea to perfectly competitive markets and demonstrates that the price premium is the return on investment in reputation. Allen (1984) shows that while warranties signal quality, consumer moral hazard leads producers to offer partial warranties, which do not eliminate the role of reputation in signaling product quality.

In this paper, we advance a model in which physicians synthesize signals for quality through their outcomes into a stock of peer reputation, characterized by patient volume and difficulty of surgical cases.⁴ The model predicts that surgeons with high peer reputations choose a lower average case difficulty relative to those with low peer reputations and that a new technology that improves the probability of success is adopted more rapidly by high peer reputation surgeons than by low peer reputation surgeons.

To test the model's predictions, we study the extent of new technology use by Florida-based surgeons who treated abdominal aortic aneurysms (AAAs) between 1992 and 2006. September 1999 marks the advent of endovascular aneurysm repair (EVAR) using AAA stent grafts, which constituted an alternative to open surgery, by using a minimally invasive technique. Adoption of the new technology requires substantial investment in specific human capital and influences the mechanism for building peer reputation and, hence, may affect surgeons' adoption timing.

AAAs are an important cause of morbidity and mortality, with over 200,000 new diagnoses each year and 15,000 deaths annually, disproportionately affecting those over the age of 60. Correspondingly, surgeons perform 55,000 repairs of which 45,000 are elective on a yearly basis (Fleming et al. 2005).

We find evidence supporting the quality signaling mechanism underlying our theory, even when controlling for the physician's focus (share of AAA cases), years in practice, board certification, and fellowship indicators. Specifically, we find that surgical success builds volume faster on relatively difficult cases, whereas surgical failures deplete volume faster on relatively easy cases. For example, an increase of one standard deviation in the success rate on relatively difficult cases leads

³ A notable exception, in the case of investment in advertising, can be found in Ehrlich and Fisher (1982).

⁴ To best understand the mechanism underlying the synthesis of outcomes into signals for quality, we conducted a series of semistructured interviews with surgeons in both the academic and community settings. The set of questions focused on peer reputation definition and building, surgery allocation across physicians and the influence of referrals and scheduling, learning and specialization, and institutional reputation vs. reputation. Repeated thematic commonalities guided our formulation of the conceptual framework.

to a 9.1 percent increase in case volume the next year, controlling for the overall success rate. Furthermore, a one-standard-deviation increase in the failure rate on relatively easy cases increases the likelihood that a surgeon permanently quits AAAs by 0.51 percent. This highlights the role of rare events (i.e., success on difficult cases or failure on easy ones) in forming a signal for quality. We also show evidence, consistent with our qualitative interviews, that the decision to adopt the technology under study is made largely by individual physicians.

There seems to be substantial heterogeneity in the characteristics of early versus late physician adopters (Escarce 1996). For example, age and years since completion of medical school are inversely correlated to adoption, whereas board certification, higher reimbursement levels, specialization, and larger practices are associated with greater adoption (Freiman 1985; Escarce et al. 1995). Our model suggests that the timing of adoption and subsequent intensity of use are sensitive to peer reputation above and beyond traditional measures of human capital and is manifested through the surgeon's choice of patient case mix severity. When testing our theoretical predictions regarding the adoption of EVAR by surgeons, we find that a one-standard-deviation increase in case mix causes between a 1 and 2.3 percent reduction in use of the minimally invasive technique (corresponding to a range of definitions for technology adoption).

II. Theory

New medical technologies are thought to improve patient outcomes, reduce treatment costs, and/or expand the appropriate set of users. They may confer benefits to patients who would or would not have otherwise been treated with the old technology. Individuals excluded from the old technology may constitute both severely ill patients who would not tolerate the old technology and relatively healthy patients who were unwilling to bear its risk beforehand.

One way in which a new technology can reduce costs is by shortening procedure time. As long as the supply of patients is not perfectly inelastic, this reduction will result in higher case volume for the individual physician.

Technology adoption requires physicians to incur an investment cost, which includes the cost of equipment and that associated with learning. This investment involves uncertainty with regard to quality, the appropriate patient population, and the chance that the technology is removed. A high degree of uncertainty lowers the attractiveness of early adoption.

As time progresses and experience with the technology accumulates, much of the uncertainty around the quality of the technology, its target patient population, and the effective ways to learn its associated techniques is resolved. The decrease in learning costs will be substantial,

especially when the new technology changes the practice of medicine and requires a new set of skills. Such skills may be considerably different in nature compared to the traditional skills required in the particular surgical discipline.

In evaluating the influence of physician peer reputation on the decision of when to adopt a new technology, we first consider the mechanism behind reputation building. This part of the model develops a conceptual framework for the formation and dynamics of peer reputation.

A. *Reputation Formation and the Signaling of Quality*

Patients select physician specialists primarily through formal networks (e.g., primary care networks, insurers, etc.) in which referrals play an important role. The more complex the patient's condition, the greater the value of employing these formal networks to ensure the best match between the patient and a physician.

The mechanism through which physicians accumulate patient volume is attracting referrals from their peers based, in part, on their perceived quality.⁵ Case difficulty (e.g., patient severity) and outcomes are the most observable signals colleagues receive about a physician's quality and therefore the most important determinants of reputation among peers. The stock of peer reputation for each physician is defined as a profile of signals resulting from the interaction between case difficulty and patient outcome. Successful medical interventions enhance the physician's peer reputation whereas failure in such interventions reduces his or her peer reputation.

There is a growing economic literature on biased attribution tendencies regarding success and failure (Benabou and Tirole 2002). Van den Steen (2004) shows that even perfectly Bayesian-rational agents will tend to attribute success to their own skills and failures to bad luck. While this growing literature highlights systematic biases in people's ability to relate outcomes to skill and/or luck, it is mostly concerned with how individuals perceive themselves and not how they are perceived by others. Empirical evidence suggests that skill is a key determinant of success (e.g., Gompers et al. 2006) and failure (e.g., Carhart 1997; Cuthbertson, Nitzschea, and O'Sullivan 2008), and therefore observers would tend to associate both positive and negative outcomes with ability. Similarly, little is known about how attribution tendencies vary with the level of task difficulty; however, informational content of any realization should be directly related to its likelihood and expectation.

In particular, peer reputation will be more sensitive to relatively rare

⁵ Garicano and Santos (2004) propose a different mechanism for within-firm referrals, governed by the firm, and based on the notion of efficiency in production (i.e., matching task to talent).

events, such as succeeding on a difficult case or failing on an easy one. These attribution tendencies of peer physicians are stronger under imperfect risk adjustment, small patient census of each surgeon, imperfect information flow within networks, greater heterogeneity in surgeons' quality, and risk aversion of referring physicians.⁶

For simplicity, consider an individual surgeon i 's performance, measured by success rate p^i , on a set of cases. As above, p^i involves both the influence of skill and randomness on outcomes. Specifically, assume $p^i = f(p, \theta^i, \mu)$, where p is the a priori risk-adjusted average probability of success across surgeons, θ^i is individual ability (or skill), and μ is a patient/environment idiosyncratic shock. While peers observe these outcomes, their attribution tendencies and a low patient census for each physician preclude precise decomposition of p^i into individual skill and unobserved external factors.⁷ Therefore, surgeon performance influences the value of the reputation signal attributed to success and failure.

The reputation benefit, B , is a function of success and failure signals, both involving p and the deviation of p^i from p :⁸

$$B(p^i, p) = \begin{cases} \frac{p^i - p}{p} & \text{if } p^i \geq p \\ \frac{p^i - p}{1 - p} & \text{if } p^i < p. \end{cases} \quad (1)$$

This formulation is consistent with greater quality attribution to rare events, where the attribution tendencies are manifested through different treatment of success and failure. Stated differently, when the discrepancy between realized success and the probability of success is large and positive (negative), it sends a strong positive (negative) reputational signal.

As expected, the derivative of B with respect to p^i is positive, since physicians who enjoy greater realized success will have a larger reputational gain:

$$\frac{\partial B(p^i, p)}{\partial p^i} = \begin{cases} \frac{1}{p} > 0 & \text{if } p^i \geq p \\ \frac{1}{1 - p} > 0 & \text{if } p^i < p. \end{cases} \quad (2)$$

⁶ We find strong support for this sensitivity (see table 3 below and its discussion).

⁷ Early career failures may discourage referring physicians from waiting for the sample size to grow enough to infer skill vs. luck since the process itself may endanger their patients. This may induce physicians with early failures to cease practice of certain procedures. We find clear evidence to support this.

⁸ To simplify our notation we do not carry the superscript i for the reputational benefit, B .

More important, the derivative of B with respect to p is always negative:

$$\frac{\partial B(p^i, p)}{\partial p} = \begin{cases} \frac{-p^i}{p^2} < 0 & \text{if } p^i \geq p \\ \frac{p^i - 1}{(1 - p)^2} < 0 & \text{if } p^i < p. \end{cases} \quad (2')$$

For simplicity, we partition cases into two mutually exclusive categories: hard cases (H), where p is relatively low, and easy cases (E), where p is relatively high. Under the formulation in (1) we obtain strong positive (negative) reputational signals from success (failure) on hard (easy) cases and weak positive (negative) reputational signals from success (failure) on easy (hard) cases, such that $B_H > B_E$ (see eq. [2']).

High-ability physicians will have higher B_H and higher B_E for a given case compared with low-ability physicians, but as long as the effect of ability on outcome is independent of the task difficulty, the resulting ordering is preserved throughout the ability distribution.⁹ Stated differently, high-ability physicians can enhance their reputation faster than those with low ability.

For a set patient census, the signaling mechanism implies an optimal mix of hard and easy cases (i.e., case mix). We define a physician's case mix, c_t , at time t , as the share of hard cases out of all cases, $c_t = H_t/(H_t + E_t)$. Success on hard cases builds volume faster than success on easy cases, and failure on easy cases depletes volume faster than failure on hard cases. Physicians, therefore, retain an incentive to influence their case mix and thereby manage their reputation as is most advantageous to their objective.

Realization signals are dynamically codified into a stock of peer reputation, through the following law of motion:

$$R_{t+1} = R_t + \phi(H_t, E_t), \quad (3)$$

where $\phi(H_t, E_t)$ is the change in reputation in period t , which will depend on the magnitude of case-specific reputational benefits, B_H and B_E , weighted by the respective number of hard and easy cases:

$$\phi(H_t, E_t) = B_H \cdot H_t + B_E \cdot E_t. \quad (4)$$

We assume that peer reputation begins to build from zero once the physician's training is completed. In each period t , all physicians in our model affect their peer reputation stock by influencing their patient case mix, c_t . While reputable physicians are often in a better position

⁹ While our model ignores the case of multidimensional ability, there is no reason to think that high-ability surgeons are better at hard cases and worse at easy cases compared with their low-ability counterparts (as in the case of fishermen and hunters). If that were the case, the notion of reputation would be task specific and may lead to different results.

to select specific cases, younger (and less reputable) physicians can influence their case mix by disproportionately covering the hospital emergency room or specializing in procedures and technologies that favor specific patient severity profiles.

For tractability, we ignore the case in which the probabilities of success and failure are endogenously determined by the physicians' experience. Abstracting away from learning will not alter the model's basic predictions if physicians' human capital is transferable across easy and hard cases or if learning is more important for hard cases than for easy ones. This assertion is reasonable since what makes easy cases easy is that they are predictable and standard, and by the time a physician's training is completed, the scope for learning is limited, especially when compared to difficult cases.¹⁰ In essence, our model tracks human capital accumulation in a more flexible way, allowing the volume of easy and hard cases to accumulate separately and permitting the outcome, success or failure, to have a differential effect on future volume. Experience and peer reputation are clearly related since reputation cannot be built without experience. However, physicians with similar experience may have vastly different levels of peer reputation, depending on their performance histories.

The physician's objective function is to maximize lifetime utility from income, subject to a time constraint. Income is the product of the total number of hard and easy cases multiplied by a fixed physician payment per procedure, \bar{D} :¹¹

$$\begin{aligned} \max_{H_t, E_t} \sum_t u(I_t) &= \sum_t u[(E_t + H_t) \cdot \bar{D}] \\ \text{subject to } T(R_t) &\geq t_E \cdot E_t + t_H \cdot H_t, \\ R_{t+1} &= R_t + \phi(H_t, E_t). \end{aligned} \quad (5)$$

The time constraint, $T(R_t)$, is monotonically increasing and concave in mapping peer reputation level to operating room (OR) time; higher reputation leads to a larger referral base, more influence on OR scheduling, permission to simultaneously run multiple ORs, and so forth. Given the bounded nature of time per day, $T(R)$ is bounded above by \bar{T} . Correspondingly, there exists an \bar{R} such that, for $R > \bar{R}$, $T(R) = \bar{T}$. We define t_H as the time needed to perform a hard procedure and t_E as the time needed to perform an easy procedure. By definition, the more difficult the case, the more time it consumes ($t_H > t_E$).

¹⁰ In the limiting case in which learning is more meaningful on easy cases than on hard ones, learning provides a competing mechanism for volume building. When learning affects volume more than reputation, some of the model's predictions are not valid. Furthermore, this scenario is not likely to be depicted in our empirical application.

¹¹ While hospital payments often adjust for severity, it is less common for physician payments. Our predictions are robust to differential payment by severity as long as the severity adjustments do not make surgeons indifferent between hard and easy cases. Moreover, in our empirical application, physician payments do not vary by severity.

For simplicity, we ignore any labor-leisure trade-offs by assuming that, regardless of reputation level, the amount of time spent working is fixed. In other words, physicians with low volume do not enjoy larger amounts of leisure by virtue of doing less volume. The residual non-OR working time ($T_{\max} - T(R)$) is spent on low-revenue and nonreputation signal-generating activities that do not provide direct utility (e.g., dedicating time to building their practices).

The physician's task can be expressed as a standard optimal control problem with the control variables being the number of H_t and E_t cases and the state variable being the stock of peer reputation, R_t . Substituting in the time constraint from (5) in terms of E_t , we obtain the following Bellman equation:

$$\begin{aligned} V(R_t) &= \max_{H_t} [u(I(H_t, R_t))] + \beta \cdot V(R_{t+1}) \\ &= \max_{H_t} \left[u \left(\left[\frac{T(R_t) - t_H \cdot H_t}{t_E} + H_t \right] \cdot \bar{D} \right) + \beta \cdot V(R_{t+1}) \right]. \end{aligned} \quad (6)$$

The first-order condition is

$$[H_t] \quad \frac{\partial u(I(H_t, R_t))}{\partial H_t} \cdot \left(1 - \frac{t_H}{t_E} \right) \cdot \bar{D} + \beta \cdot V'(R_{t+1}) \cdot \frac{\partial R_{t+1}}{\partial H_t} = 0, \quad (7)$$

and the envelope condition is

$$\begin{aligned} [R_t] \quad V'(R_t) &= \frac{\partial u(I(H_t, R_t))}{\partial R_t} \cdot \left[\bar{D} \cdot \frac{T'(R_t)}{t_E} \right] + \beta \cdot V'(R_{t+1}) \\ &\quad \cdot \left[1 + \frac{\partial \phi(H_t, E_t)}{\partial R_t} \right]. \end{aligned} \quad (8)$$

Using the first-order and envelope conditions, we obtain the following Euler equation:¹²

$$u'(I_t) = \beta \cdot u'(I_{t+1}) \cdot \left[1 + T'(R_{t+1}) \cdot \left(\frac{B_H - B_E}{t_H - t_E} \right) \right]. \quad (9)$$

Conceptually, equation (9) introduces a simple intertemporal trade-off between *investment* and *consumption* in standard growth theory by highlighting the trade-off between relatively low-profitability hard cases that build future procedural volume and more profitable easy cases that do not. The direct utility change in period t equals the discounted direct utility change in period $t + 1$ multiplied by the return to investment through the choice of case mix. The rate of return is a product of two

¹² See App. A for a derivation

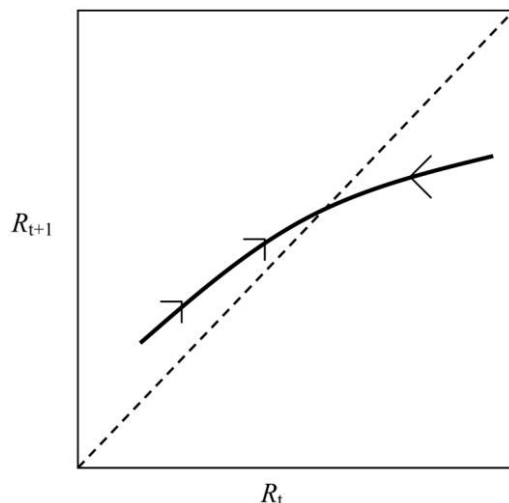


Figure 1.—Phase diagram for intertemporal reputation

terms: the sensitivity of volume to reputation (measured in units of time) and the ratio of relative benefits to relative costs of hard and easy cases.

To keep the solution as general as possible we apply the contraction mapping theorem in the context of (9) to guarantee a numerical solution (Judd 1998). Our state space R is compact and the modulus $\beta < 1$; these conditions guarantee that we have a contraction that is monotone in V and has a unique fixed point.¹³

Figure 1 illustrates the phase diagram for reputation with a stable and nonoscillatory equilibrium. In equilibrium physicians choose a case mix that ensures the same level of peer reputation (i.e., $R_t = R_{t+1}$).

This analysis is similar to some studies focusing on decisions made earlier versus later in a person's career and arguing that in equilibrium the incentives for the employees are to work hardest (Holmstrom 1999) or choose riskier projects (Diamond 1989) in the beginning of their careers. Diamond also emphasizes the role of reputation in the development of the equilibrium path.

Figure 2 shows the time path for choice of hard and easy cases along with the total number of cases performed. Early in the physician's career the hard caseload rises as rapidly as possible and then slowly begins to diverge to the steady-state value that keeps reputation constant. The easy case path is pegged at zero at first and then increases until it reaches the equilibrium value. As a result, case mix, c_t , is near one early in the time path and decreasingly converges to a steady-state value.

¹³ Under a specific (and simplified) assumption regarding the functional form of $u(J)$ and $T(R)$, a closed-form solution is available.

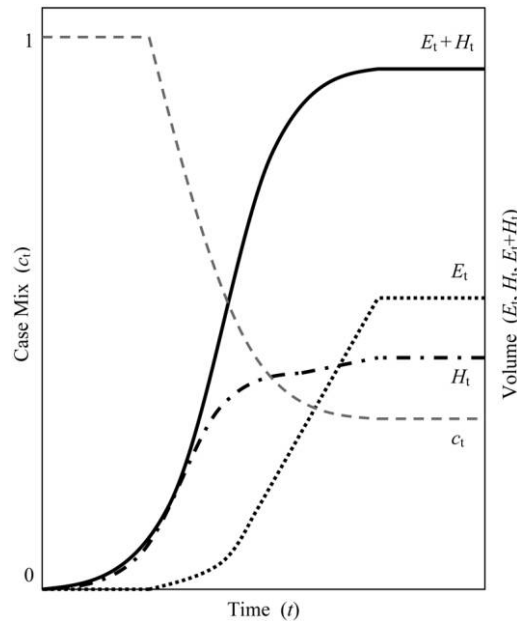


Figure 2.—Time path of the case choice

B. *The Timing and Extent of Technology Adoption*

Using our conceptual framework for the formation and dynamics of peer reputation, which is manifested through patient volume and case mix, we evaluate the influence of peer reputation on the decision of when to adopt a new technology. With steady entry of physicians into the profession, the technology introduction will find individual physicians at various locations along the optimal reputation path based on the length of their careers and their practice experiences (outcome realizations).

The adoption of a new technology shifts the probability of success upward and the expected reputational benefit downward and therefore weakens the reputation-building mechanism. Success on hard cases may no longer constitute a rare enough event, and failure on easy cases will carry a bigger reputational penalty. Therefore, physicians who can benefit from rapid increase in their reputation stock will choose to delay the adoption of the new technology (i.e., through their choice of cases).

It is important to notice that while the new technology may weaken reputation-building signals, it may not be clinically superior for all patients. For example, a new technology may lower both the surgical risk and the definitiveness of the treatment in a way unattractive to patients with low surgical risk. Therefore, the new technology does not render the old one obsolete and would not lead physicians to violate their

patients' trust by delaying its adoption.¹⁴ The mechanism through which physicians delay the adoption of the new technology is to gravitate toward patients still suitable for the old procedure.

The physicians who are in steady state choose a fixed case mix. The decision to adopt will be an optimal stopping problem in which the physicians weigh the income benefit of switching to the new technology (and converging to the new reputation equilibrium) versus the fixed cost of adoption (which will be decreasing over time).

As in Klausen, Olsen, and Risa (1992), physicians in steady state compare the present value for the income stream under the new technology with the one from the old technology. Technology adoption will affect the physician's income stream through three different channels: the change in patient volume, corresponding to the new equilibrium level of reputation; the allocation of time in the steady-state case mix; and the profitability of hard and easy cases under the new technology (i.e., decrease in procedure length). The time period at which the present value of the incremental income stream under the new technology is equal to the cost of adoption will identify the optimal time of adoption.

In analyzing the decision of when to adopt, we establish a reference point from which adoption is a feasible element in the choice set: the time of introduction, t_i . The time elapsed since the time of introduction is $t - t_i$, and its corresponding cost is $C(t - t_i)$. For simplicity, we treat the cost of adopting the technology as a decreasing and convex function $C(\cdot)$ (i.e., $C'(\cdot) < 0$ and $C''(\cdot) \geq 0$).¹⁵ This convexity can be motivated in several ways: as time elapses and more physicians adopt the technology, the price of the equipment decreases more slowly, new information about the technology comes to bear more infrequently, and the collective experience with the technology demonstrates diminishing marginal returns with respect to resolving uncertainty and learning. Our differential results regarding high- and low-reputation physicians hold even without adoption costs.

Consider the introduction of a new surgical technology characterized by a reduction in OR time and potentially improved patient outcomes (e.g., mortality), particularly for more difficult cases. We also assume that the reputation-driven OR time, $T(R)$, is not affected directly and independently by the adoption decision (i.e., $T(R) = \bar{T}$).

¹⁴ The case of new medical technologies rendering older ones obsolete is less appealing theoretically since the welfare implications of delaying the adoption of a superior technology are trivial.

¹⁵ An alternative cost function could rely on the number of physicians who have already adopted the technology. With heterogeneity in willingness to pay, e.g., the cost of adoption will produce identical predictions.

The discounted present value of the gain from using the new technology (in utility terms) for the simple case of an infinite horizon is

$$\begin{aligned} \Delta \tilde{u}_{\text{tech}} &= \sum_{\tau=0}^{\infty} \beta^{\tau} \cdot \Delta u_{\text{tech}} \\ &= \left(\frac{1}{1-\beta} \right) \cdot \left[u \left(\frac{B'_H - B_E}{B'_H \cdot t_E - B_E \cdot t'_H} \right) \right. \\ &\quad \left. - u \left(\frac{B_H - B_E}{B_H \cdot t_E - B_E \cdot t_H} \right) \right] \cdot \bar{T}. \end{aligned} \quad (10)$$

The adoption time, t_A , chosen by the lifetime utility-maximizing physician is obtained when $\Delta \tilde{u}_{\text{tech}} = C(t_A - t_l)$. This t_A is lower than under the finite-horizon case, so it forms a lower bound. Without adoption costs, steady-state physicians would adopt the new technology instantaneously (i.e., $t_A = t_l$).

Next we turn to physicians who have not yet reached steady state. These physicians, characterized by a lower reputation, have a smaller patient volume and therefore lower per-period income until they reach steady state. Given their limited patient volume, they may not have the ability to alter their reputation levels rapidly by shifting their case mix. Thus, by adopting the new technology they will be moving from one reputation path to a different one, while converging more slowly than if they continued to use the old technology.

Figure 3 plots the two phase lines for the old and new technologies and their corresponding steady-state levels E and E' . The steady-state peer reputation level is lower under the new technology since the cost of acquiring reputation increases. The decisive factor determining whether or not adoption will be delayed is the physician's current level of peer reputation stock. Off-steady-state physicians whose reputation level, R_{t+1} , is equal to or above the new technology steady-state level, E' , will adopt the new technology instantaneously and hence move to the new technology phase line (i.e., $t_A = t_l$). Physicians whose reputation level is strictly below E' will choose $t_A > t_l$ such that they reach $R_{t+1} = E'$ by t_A .

A corner solution exists, in which all physicians adopt the new technology at t_l , when the new technology creates efficiency gains so great that they render the reputation-building mechanism virtually ineffective. As long as adoption of technology is gradual, our theoretical analysis suggests that low-severity case mix and high patient volume are among the characteristics of early adopters.

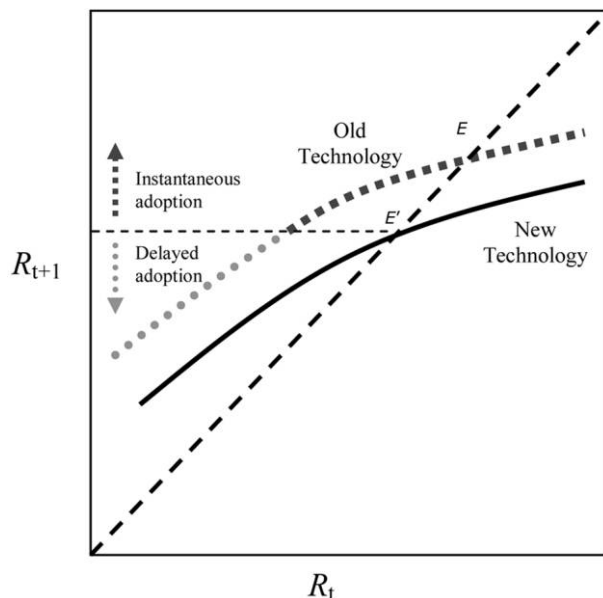


Figure 3.—Phase diagram for intertemporal reputation for different technologies

III. Empirical Analysis

We test the predictions from our theoretical framework on the timing and extent of new technology use by Florida-based surgeons who treated AAAs between 1992 and 2006. Until September 1999, surgeons repaired AAAs exclusively with traditional open surgery. Subsequently, the advent of a new technology, EVAR using AAA stent grafts, introduced a choice between the technologies and the decision of when to adopt.

Surgeons who perform AAA repair are well suited for studying the dynamics of reputation building and technology adoption. AAA repair generates strong reputational signals, due to the combination of high risk, need for specialized human capital to address technical complexity, and elective nature of the procedure, that drive physician referrals. Furthermore, its relative infrequency makes it difficult for peers to infer whether outcomes result from skill or other factors.

EVAR for AAAs is an ideal new technology in which to study the physician technology adoption decisions. While there was considerable uncertainty around long-term mortality, the benefit of minimally invasive procedures on postoperative (short-term) mortality was already well demonstrated. In spite of the lower postoperative mortality, a corresponding compromise in the definitiveness of treatment made it unlikely to completely replace open repair techniques; literature at the time of introduction identified only high-mortality risk patients as potentially

appropriate for EVAR (Moore et al. 1999).¹⁶ While EVAR required physicians to make substantial investments in both human and physical capital, it enabled shorter procedure times with comparable physician reimbursement, thereby increasing the profitability for the adopting surgeons (Freischlag 2007).¹⁷ Finally, the reduced mortality risk with EVAR, especially on difficult cases, weakened the reputation-building mechanism, making it an appropriate technology with which to study the interplay between managing reputation and technology adoption.

A. *Data*

The data are drawn from the Florida Agency for Health Care Administration's inpatient discharge data file and the Florida Department of Health's Health Provider Information database. These data for the years 1992–2006 include 1,325 surgeons, 196 hospitals, and 45,093 nonruptured AAA records.

Together these data sources provide a comprehensive set of information on patients and the surgeons who treat them over the study period. These data sources allow tracking of physicians and linking to data on their characteristics. Furthermore, the older demographic and large population of Florida make it an ideal laboratory in which to study the impact of AAA technology since AAAs affect mostly the elderly.

The sample is limited to admissions that have an aortic aneurysm principal diagnosis (excluding ruptured aneurysm) and a principal procedure code for either open repair or EVAR.¹⁸

The old technology is used exclusively by general, vascular, and thoracic surgeons, whereas the new technology, which does not require open surgery, is also used by interventional radiologists and interventional cardiologists. The latter group is excluded (5.3 percent of phy-

¹⁶ Similarly, EVAR was not an option for infrequent anatomically complex aneurysms that involve other vasculature such as the renal arteries.

The long-term retrospective mortality comparisons between EVAR and open repair produced mixed results, and clinical guidelines were debated throughout the study period (Lederle 2004). However, the motivation for EVAR use was almost exclusively based on improved short-term postoperative mortality.

¹⁷ In contrast to physicians, there was considerable debate on the profitability of EVAR vs. open repair at the hospital level. When considering opportunity costs from increased volume, EVAR was suggested as more profitable than open repair (Rosenberg et al. 2005). Hospitals did, however, need to institute catheterization labs in which surgeons could operate. We demonstrate that our results are robust to accounting for the existence of catheterization labs in hospitals.

¹⁸ Aortic aneurysm admissions and procedures are identified with principal diagnoses with the following codes from the International Classification of Diseases (ICD-9): 441.0–441.9 and ICD-9 procedure codes 38.44, 38.45, 39.25, 39.71, and 39.73. Our results are robust to the inclusion of ruptured aneurysm cases (ICD-9 codes 441.1, 441.3, 441.5, and 441.6).

sicians in the sample) since the paper focuses on technology-switching behavior.¹⁹

Our outcome measure, in-hospital mortality, is an appropriate measure of the short-term postoperative mortality germane to the theory. This measure is commonly used for studying surgical procedures, is likely to be observed by peer surgeons, and is prevalent in the data (5.44 percent in-hospital death rate). Our results are robust to modifications of the outcome measure using both prolonged length of stay (PLOS) and PLOS plus in-hospital mortality as the marker for failure. PLOS is utilized because it is a validated marker for complications (Silber et al. 1999).

We partition cases into hard and easy by mortality risk based on patient characteristics at the time of admission (Khuri et al. 1997).²⁰ Risk scores are created using out-of-sample data to avoid the problem of a generated regressor (Pagan 1984). The standard patient risk model employs a logistic specification:

$$\Pr\{\text{death}\}_i = \Lambda(\beta_1 \cdot \text{age}_i + \beta_2 \cdot \text{male}_i + \gamma \cdot E_i).$$

The dependent variable death_i is an indicator variable equal to one if the patient died during the hospital admission and zero if he or she was discharged alive. The variable age_i is the age of the patient, and male_i is an indicator for the sex of the patient being male. The term E_i is the set of 27 Elixhauser comorbidities used as clinical predictors of probability of death (Elixhauser et al. 1998). From these variables, we compute the predicted mortality (risk-adjusted mortality) of each patient and assign each patient into the *easy* and *hard* categories.²¹

Figure 4 plots the probability of survival by year, case severity, and technology. The probability of survival for hard cases is lower than for easy cases, regardless of the technology used, supporting the risk stratification methodology. Moreover, there is dramatic improvement visible in mortality for hard and easy patients; average survival rates for hard cases increased from 88.7 percent to 97.1 percent, whereas for easy cases survival improved from 96.7 percent to 99.4 percent.

¹⁹ We exclude a set of anatomically complex AAA cases for which endovascular repair was not an option (ICD-9 procedure codes 384.6 and 384.7).

²⁰ Our results are robust to alternatively defining emergent cases as hard and elective cases as easy, an almost orthogonal classification (correlation .12) as may be expected. Emergent cases can be more difficult for both clinical (time sensitivity secondary to rapid hemorrhage) and nonclinical reasons (timing of admission, staffing). Mortality risk likely increases case difficulty through other mechanisms. For example, greater comorbidity may require an expeditious pace (reduced tolerance to clamping of the aorta and to keeping anesthesia load low), may result in a more friable aneurysm (e.g., diabetic patients), and likely necessitates more precise suturing.

²¹ On the basis of this variable, the patients are categorized into identical buckets in the same proportions as the risk of mortality variable (23.75 percent minor, 27.33 percent moderate, 24.59 percent major, and 24.33 percent extreme). The minor and moderate categories are combined into easy cases and the major and extreme classifications form the hard cases.

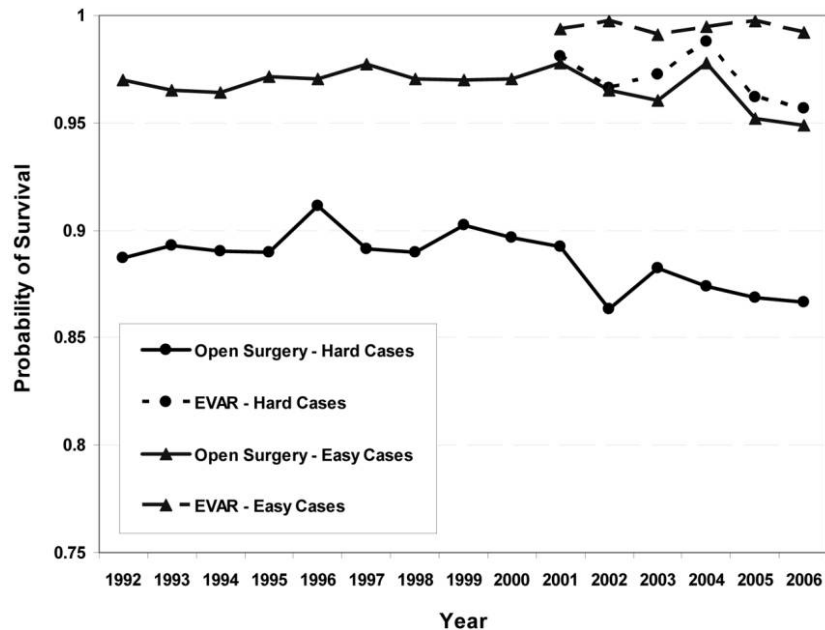


Figure 4.—Probability of success by case type and technology, 1992–2006

Table 1 provides summary statistics for the surgeons in our sample. Means and standard deviations are reported for the full sample (1,325 surgeons) and separately for 497 high-volume surgeons and 828 low-volume surgeons.²² High-volume surgeons have, on average, longer tenure than low-volume surgeons; however, the difference is not statistically significant.²³ Similarly, there is little difference in academic medical center affiliation on the patient volume gradient. Vascular surgeons are more likely to be high-volume surgeons. The magnitude of difference in volume is very large, with high-volume surgeons performing almost six times as many AAA procedures in an average year than low-volume surgeons (8.7 procedures vs. 1.4).

Consistent with a large body of literature on the relationship between volume and outcome, we find high-volume surgeons to have a higher overall surgical success rate compared with their low-volume counterparts (Luft and Maerki 1987; Gaynor, Seider, and Vogt 2005). In addition, they are much more likely to succeed on a hard case and less

²² On the basis of interviews and subject to sensitivity analysis, low-volume surgeons are defined as those performing fewer than three AAA repairs in most years of our sample and never above six AAA procedures. High-volume surgeons are defined as those performing six or more AAA repairs for most years of our sample. This definition partitions the full sample because of low within-surgeon volatility over time.

²³ We find years of experience to be positively correlated with volume and negatively correlated with case mix, as the theory suggests.

TABLE 1
SUMMARY STATISTICS

Characteristic	Full Sample	Low-Volume MDs	High-Volume MDs
Experience (years)	12.9 [8.6]	12.4 [8.8]	13.8 [8.3]
Academic medical center appointment (%)	21	21	21
Graduate medical education (%):			
General surgery (only)	63	73	58
Vascular surgery	16	7	21
Thoracic surgery	21	20	21
Board certification (%):			
General surgery	46	35	47
Vascular surgery	10	3	21
Thoracic surgery	21	14	32
Other or no board certification	23	48	0
AAA volume	6.1 [7.9]	1.4 [1.2]	8.7 [8.8]
Case mix	.44 [.3]	.46 [.43]	.44 [.26]
Overall success rate (%)	89 [21]	86 [29]	90 [16]
Success rate on hard (%)	83 [29]	80 [37]	84 [25]
Failure rate on easy (%)	5 [18]	9 [26]	4 [13]
AAA share (%)	3 [6]	3 [8]	4 [4]
Cumulative share of EVAR, after introduction (%)	24 [31]	21 [37]	24 [29]
Number of hospitals with OR privileges	1.4 [.8]	1.3 [.6]	3.1 [1.3]
Number of surgeons	1,325	828	497
Number of surgeon-years	7,309	2,603	4,706

Note.—Standard deviations are in brackets.

likely to fail on an easy case. Finally, lower case mix is associated with higher patient volume.

Table 2 provides summary statistics for the patient population in our sample, unadjusted for surgical risk and provider characteristics. The table reports separate statistics for the periods before and after the availability of EVAR and further partitions patients treated in the post-innovation period into those treated using open surgery (10,783 patients) and those treated using EVAR (9,459 patients). Faced with the choice of technology, patients who underwent open procedures were younger than those treated with EVAR. This is not surprising since minimally invasive techniques were, in part, targeted for older patients with higher surgical risk. Finally, the use of EVAR is associated with lower mortality (1.5 percent vs. 6.9 percent) and shorter hospital stays (4 vs. 10.5 days).

TABLE 2
 PATIENT CHARACTERISTICS BY PROCEDURE AND TIME PERIOD

Characteristic	1992:1–2000:3	2000:4–2006:4	
	Open (<i>n</i> = 24,851)	Open (<i>n</i> = 10,783)	EVAR (<i>n</i> = 9,459)
Patient age (years)	71.05 [9.7]	69.75 [12.6]	73.94 [8.5]
Female (%)	21	25	15
White (%)	92	87	91
Number of Elixhauser comorbidities:			
% of patients with 0	15	8	11
% of patients with 1	36	24	30
% of patients with 2	35	31	31
% of patients with 3 or more	14	37	28
Three strongest mortality-associated Elixhauser comorbidities:			
% of patients with coagulopathy	7	12	4
% of patients with congestive heart failure	.4	.6	.2
% of patients with renal failure	3	6	5
Mortality rate (%)	6.3	6.9	1.48
Length of stay (days)	10.22 [7.94]	10.5 [10.86]	3.86 [4.96]

Note.—Standard deviations are in brackets.

Surgeon adoption of new technology was gradual over the sample period. Using a stable panel of surgeons who performed AAA repairs prior to the introduction of EVAR and continued to operate throughout the subsequent sample period, figure 5 plots the share of surgeons who have adopted the new technology by year and quarter. In the fourth quarter of 2000, one year after EVAR was introduced, a procedure code was assigned, enabling tracking of EVAR procedures. At that point in time 17.7 percent of surgeons had already adopted EVAR. By the end of 2006, following steady adoption, 80.8 percent of surgeons had treated patients with the new technology. This finding is consistent with previous studies of technology adoption by surgeons (Escarce et al. 1995; Escarce 1996).

The decision to adopt AAA stent grafts is largely made by individual surgeons and to a lesser degree by the institutions with which they are affiliated. Even though the adoption of EVAR generally requires an in-hospital catheterization laboratory, a decision that is primarily at the hospital's discretion, our findings are robust to the existence of such labs. In Appendix B we present some evidence consistent with surgeon-level adoption.

B. Reputation Formation and the Signaling of Quality

This subsection evaluates the reputation-building mechanism that underlies the subsequent technology adoption analysis and corresponds

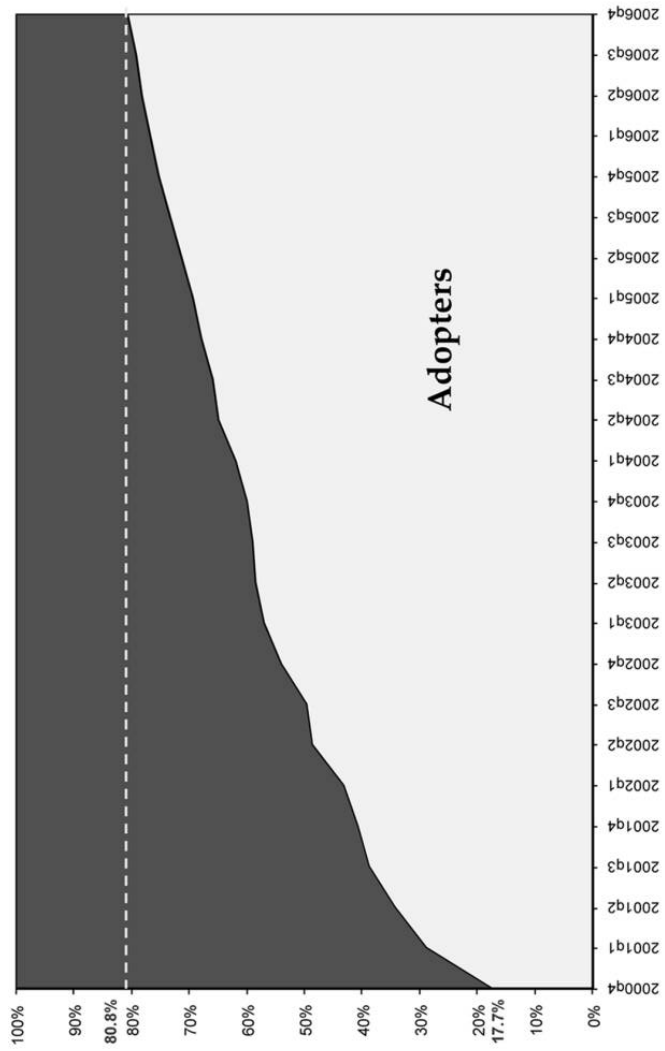


Figure 5.—Share of surgeons who have adopted EVAR using AAA stent grafts

to the theoretical discussion in Section II.A. Specifically, we test that succeeding on difficult cases builds volume more rapidly than succeeding on easy cases and that failing on easy cases depletes volume more rapidly than failing on difficult cases.

To do this we pursue six different specifications. The first specification, in equation (11), identifies the effect of replacing a failure with a success on a hard case on the next period's volume:

$$\begin{aligned} \text{Volume}_{i,t} = & SH_{i,t-1} \cdot \alpha + SE_{i,t-1} \cdot \beta + FE_{i,t-1} \cdot \delta + W_{i,t-1}\gamma + Y_t \\ & + MD_i + \varepsilon_{i,t-1}, \end{aligned} \quad (11)$$

where $\text{Volume}_{i,t}$ is the physician-year specific AAA volume in the current year; $SH_{i,t-1}$ is the 1-year lagged number of successes on hard cases; $SE_{i,t-1}$ and $FE_{i,t-1}$ are the lagged number of successes and failures on easy cases, respectively; $W_{i,t-1}$ are time-varying surgeon-level controls including lagged AAA volume, lagged case mix index, lagged share of AAA cases out of all cases, and years of experience; Y_t is a set of year dummies; and MD_i is a set of individual surgeon fixed effects.

The coefficient on $SH_{i,t-1}$ captures the effect of turning a failure on a hard case into a success on a hard case. This is the case since both volume and case mix are held constant. The expected sign on α is positive according to the predictions from theory.

Similarly, we employ a second specification in which we identify the volume effect of replacing a success with a failure on an easy case. In this specification success on easy cases is the reference group, and the sign of the coefficient estimate is expected to be negative.

A third specification combines the two elements discussed in the first two specifications by representing success and failure using rates. The success rate on hard cases and the failure rate on easy cases are used as regressors:

$$\begin{aligned} \text{Volume}_{i,t} = & SH_Rate_{i,t-1} \cdot \alpha + FE_Rate_{i,t-1} \cdot \beta + W_{i,t-1}\gamma + Y_t \\ & + MD_i + \varepsilon_{i,t-1}, \end{aligned} \quad (12)$$

where $SH_Rate_{i,t-1}$ and $FE_Rate_{i,t-1}$ are the lagged fractions of successes on hard cases and failures on easy cases, respectively. All controls are identical to the prior specifications. In this equation, α identifies the effect of success rates on hard cases, for which we expect a positive sign, and β identifies the effect of failure rates on easy cases with an expected negative sign.

Our fourth specification explores the effect of the overall success (failure) rate on the change in volume regardless of case severity. Our fifth specification evaluates the volume effect from the success rate specific to hard cases beyond the surgeon's overall success rate. Our final specification evaluates the effect of the interaction between severity and case mix on future volume.

Thus far we have treated the volume effect of failure on easy cases as an intensive margin phenomenon. Alternatively, failure on easy cases may be driving attrition of surgeons from our sample. To deal with this issue, we use a stable panel of surgeons as well as replicate all six specifications using a lead variable for attrition. The dependent variable $Quit_AAA_{i,t}$ is an indicator variable that equals one if the surgeon's AAA volume is zero from the next time period onward.²⁴ We expect higher failure rates/counts to positively affect surgeon attrition.

In all specifications, surgeon fixed effects are used to account for time-invariant unobserved heterogeneity that could affect the attributions of quality. This helps mitigate concerns that the relationship between lagged performance and volume observed in the cross section is driven by composition effects, ensuring that the performance parameters in (11) and (12) are identified from changes in volume within surgeons. Following Gibbons and Bhaumik (2001), regressions are weighted by volume.

The results from estimating the six specifications are summarized in table 3.²⁵ Rows correspond to specifications 1–6 and report the coefficient estimates of interest. Column 1 reports results for the full sample; columns 2 and 3 report results separately for low- and high-volume surgeons; columns 4 and 5 report results separately for procedures using the old and the new technologies; column 6 reports results for the full sample and uses the lead of surgeons' attrition (quit AAA in next period) as the dependent variable; finally, column 7 reports results for the stable panel of surgeons who perform AAA procedures throughout the sample period (stayers).

We find that success has a positive effect on future volume, with a one-standard-deviation improvement in the overall success rate leading to a 6.7 percent increase in next period's number of AAA cases. There is also evidence that success on hard cases builds volume; replacing a single failure with a success on a hard case improves future AAA volume by 0.17 case. The third specification suggests that a one-standard-deviation increase in success rate on hard cases leads to an approximately 5.7 percent increase in next period's number of AAA cases. Success on hard cases is shown to be important for building future volume even when we control for overall success rates, supporting the reputation-building mechanism described in Section II.A. Specifically, improving the hard case specific success rate by one standard deviation leads to a 9.1 percent increase in next period's number of AAA cases.

The volume effects of failure on easy cases are mixed. In the case of

²⁴ The bulk of surgeons who stop doing AAA procedures neither relocated away from Florida nor left the profession but rather continued to perform non-AAA operations.

²⁵ All results are robust to the inclusion of hospital fixed effects and alternative risk identification strategies, such as using a patient risk model based on other vascular conditions and using emergent cases as hard. We also perform a Hausman test on the fixed-effects models and reject the absence of endogeneity.

surgeons using the new technology, failure tends to deplete subsequent volume. Our theoretical predictions suggest a higher penalty for failure with the new technology compared to the old technology.²⁶ While this is true in some specifications in the old technology sample, in some cases we find a positive association between failure and future volume. These results are likely to reflect a spurious correlation driven by attrition of poor performers. A closer look at attrition (col. 6) suggests that this is indeed the case, with failure on easy cases leading to a higher probability of quitting AAA procedures. Even when we control for the overall failure rate, a one-standard-deviation increase in the failure rate on easy cases increases the likelihood of a surgeon abandoning AAA repairs by 0.51 percent. Furthermore, limiting the analysis to the subsample of stayer surgeons reverses the sign on the coefficient estimate on failure on easy cases. Replacing a success with a failure on an easy case, for stayer surgeons, causes a reduction in 0.5 AAA case in the next period.

C. *The Timing and Extent of Technology Adoption*

This subsection tests our prediction that high-reputation surgeons, characterized by a relatively low case mix and high volume, will adopt a new technology faster than low-reputation surgeons. We evaluate the effect of case mix and volume on the timing of adoption using four estimation models: cross-sectional, hospital fixed effects, surgeon fixed effects, and hospital-surgeon fixed effects. The estimation equation is

$$\begin{aligned} \text{Adoption}_{it} = & \text{Case mix}_{it} \cdot \alpha + \text{Volume}_{it} \cdot \beta + W_{it}\gamma + X_t\lambda + Y_t \\ & + MD_i + \varepsilon_{it}. \end{aligned} \quad (13)$$

The dependent variable, Adoption_{it} , is a measure of the level of new technology use by surgeon i in year t . For robustness, we use four different definitions of technology adoption: (1) Adoption = cumulative share of cases using EVAR, after introduction. The share of cases using EVAR is computed out of all AAA cases (using both EVAR and open repair) from the time at which EVAR was introduced. (2) Adoption = cumulative share of cases using EVAR, after the first use. This is the same as the previous definition except for the treatment of surgeons delaying adoption. Under this measure, surgeons are excluded from the sample until their first use of EVAR. (3) Adoption = share of cases using EVAR: the number of cases using the new technology out of all AAA cases performed. (4) Adoption = used EVAR ≥ 5 times. To avoid

²⁶ Note that while the larger penalty for failure on easy cases with the new technology is consistent with the theory, the larger reward for success on hard cases with the new technology is not. However, the effect of success and failure with the new technology may be correlated with the success and failure profile with the old technology and, more important, with the adoption decision itself.

TABLE 3

THE EFFECT OF LAGGED SUCCESS AND FAILURE, BY CASE TYPE, ON VOLUME
 Dependent Variable: AAA Volume/Quit AAA in Next Period

Model	Effect	Surgeons			Technology			Quit AAA in Next Period (6)	Stayers (7)
		Full Sample (1)	Low Volume (2)	High Volume (3)	Old (4)	New (> 2000) (5)	Quit AAA in Next Period (6)		
1	Effect of replacing failure with success on hard cases	.17*** [.06]	.25* [.14]	.24 [.17]	.16*** [.03]	.62*** [.04]	-.0028*** [.0006]	.17* [.07]	
2	Effect of replacing success with failure on easy cases	-1.02*** [.09]	-.05 [.15]	-.03 [.27]	-.28*** [.08]	-7.13*** [.46]	.01*** [.001]	-.06 [.1]	
3	Effect of success rate on hard cases	.97*** [.17]	.25 [.34]	.42 [.35]	.44*** [.17]	11.2*** [.69]	-.01*** [.004]	1.08*** [.23]	
	Effect of failure rate on easy cases	-1.08*** [.31]	-.4 [.49]	-.19 [.7]	-.93*** [.34]	-4.9*** [.82]	.04*** [.01]	.2 [.39]	
4	Effect of overall success rate	1.43***	.26*	.58	.18	11.6***	-.02**	.83***	

5	Effect of success rate on hard cases (failure rate on easy) controlling for overall success rate	[.27 [.25]	[.15 -.25 [.46]	[.39 .27 [.54]	[.2 .88*** [.25]	[1.11 11.5*** [.95]	[.01 .02** [.01]	[.31 1.45*** [.33]
6	Effect of interaction between success rate and case mix severity	2.38*** [.49]	.67* [.37]	3.49*** [.67]	4.1*** [.53]	22.8*** [9.36]	.02 [.04]	4.92*** [.83]

Note.—Analyses with samples 1, 4, 5, and 6 are weighted by volume; analyses with samples 2 and 3 are unweighted; all regressions include surgeon fixed effects and year dummies. Model 1 includes lagged yearly count of successes on hard cases, lagged yearly count of failures on easy cases, and lagged yearly count of successes on easy cases; model 2 includes lagged yearly count of successes on hard cases, lagged yearly count of failures on easy cases, and lagged yearly count of failures on hard cases; model 3 includes lagged yearly share of successes on hard cases and lagged yearly share of failures on easy cases; model 4 includes lagged yearly share of successes on all cases; model 5 includes lagged yearly share of successes on hard cases (lagged yearly share of failures on easy cases) and lagged yearly share of failures on all cases; model 6 includes lagged yearly case mix, lagged yearly share of successes on all cases, and the interaction between lagged yearly case mix and lagged yearly share of successes on all cases; In addition, all models control for a set of lagged variables: AAA volume, case mix, and share of all cases that are AAA (share_AAA). Robust standard errors are in brackets.

* $p < .2$.

** $p < .05$.

*** $p < .01$.

sensitivity to potential measurement error, this measure uses an indicator variable that equals one once a surgeon performs five EVAR procedures cumulatively. Moreover, for the first three fractional measures of adoption, there is a concern when using linear functional form in our fixed-effects analysis, which ignores the bounded nature of the various adoption share measures (Papke and Wooldridge 1996, 2008).²⁷ This fourth adoption model is free of the fractional response concern and serves as a robustness check for the first three measures.

As in Escarce et al. (1995), time-varying controls (W_{it}) include the surgeon's share of AAA cases out of all cases, the share of patients with commercial insurance, the percentage of patients enrolled in a health maintenance organization (HMO), and the number of years in practice; Y_t is the set of year dummy variables; and ε_{it} is the error term. The cross-sectional model includes a number of time-invariant controls (X_i): the case mix index and aggregate patient volume accumulated prior to availability of the new technology, an indicator for whether the surgeon has an appointment at an academic medical center, and dummy variables for fellowship and board certification in vascular surgery.

We allow the number of years in practice to have an independent effect on the extent and timing of adoption of the new technology. Physicians with more years in the profession will inadvertently have more years of experience with the older technology and therefore may prefer it. In addition, they may have a shorter time horizon in which to capitalize on the investment required in the new technology. These considerations may lead surgeons with longer tenure in the profession to adopt the new technology later or not at all. However, older surgeons may have large enough practices to accrue substantial gains from time-saving characteristics of the new technology. Moreover, older surgeons may better understand the limitations of the old technology, and high-volume practices are likely to include patients particularly suited for the new technology.

Table 4 reports the results from estimating equation (13) under the four estimation models. Each column reports results for four variables: case mix, lagged AAA volume, lagged AAA share of total cases, and years of experience.²⁸ For the two specifications with no physician fixed effects we also report results for board certification and fellowship in vascular surgery.

We find that the higher the lagged patient volume, the faster surgeons adopted EVAR. While this is consistent with a reputation-building mechanism, this finding is also consistent with other equally parsimonious

²⁷ Consistent results were found when using a fractional logit model.

²⁸ Findings are robust to partitioning of cases into emergent and nonemergent as well as to the inclusion of prolonged length of stay as the outcome variable (both separately and combined with mortality). Similarly, stratifying the analysis by high- and low-volume physicians did not alter the results in table 4.

mechanisms. For example, surgeons with larger practices will be able to spread the fixed cost of investment in equipment and skills across a larger patient census. The relationship between volume and speed of adoption is documented in the literature (Escarce et al. 1995; Hoppe 2002).

We find a negative effect of lagged case mix on surgeon's speed in adopting the new technology, which is robust across all estimation models and definitions of technology adoption. When we use cumulative share of cases using EVAR, after introduction the point estimate on lagged case mix (in the most saturated model) produces a highly statistically significant estimate of -0.026 . This implies that a one-standard-deviation increase in the share of hard cases leads to approximately a 1 percent decrease in the use of EVAR (measured as a share of all AAA procedures). This effect is larger using other definitions of adoption (ranges from 1 percent to 2.3 percent) and is negative and significant regardless of the estimation model. Our results were not altered by the inclusion of an in-hospital catheterization laboratory indicator.²⁹

The negative relationship between case mix and timing of adoption supports the prediction of the theoretical model in Section II.B, especially since it is not a priori obvious why for a new technology that putatively was more applicable to difficult cases, surgeons with a more severe case mix delay adoption. In addition to case mix and AAA volume, we also find that a higher share of a surgeon's practice that is dedicated to AAAs is associated with faster adoption.

As expected, the surgeon's years of experience has an independent effect on the timing of adoption, such that surgeons with more experience adopt the technology faster. In the cross-sectional and hospital fixed-effects models, none of the human capital variables (including years of experience, board certification, and fellowship in vascular surgery) were statistically significant.

IV. Discussion

This study aims to take a first step toward understanding the role of peer relations in the provision of physician services. The links between surgical success and volume building, as well as between failure and volume depletion and attrition, indicate responsiveness to the quality information contained in outcomes. The market seems to punish failing surgeons with an emphasis on those who fail on easy cases and reward more generously those who succeed on relatively difficult cases. This

²⁹ In the most saturated version of the model, where both surgeon and hospital fixed effects were included, the effect of lagged case mix almost doubles in magnitude when including an in-hospital cardiac catheterization laboratory indicator. This indicator variable is time varying since the share of general hospitals with catheterization labs increased from 47 percent in 1992 to 73 percent by 2006.

TABLE 4
THE EFFECT OF LAGGED CASE MIX ON THE TIMING OF TECHNOLOGY ADOPTION

Explanatory Variable	OLS	Hospital	Physician	Physician +
		Fixed Effects	Fixed Effects	Hospital Fixed Effects
A. Dependent Variable: Cumulative Share of Cases Using EVAR, after Introduction				
Case mix lagged	-.058* [.036]	-.048** [.02]	-.025*** [.004]	-.026*** [.004]
AAA volume lagged	.0085*** [.002]	.004*** [.001]	.00060*** [.0001]	.0007*** [.0001]
AAA share of total cases lagged	.66 [.5]	1.24*** [.3]	.48*** [.04]	.47*** [.03]
Years of experience	.0027 [.0022]	-.0011 [.0017]	.0325*** [.0004]	.0327*** [.0005]
Board certification	.0014 [.0385]	-.0147 [.02767]		
Fellowship	-.0303 [.04331]	-.0223 [.0276]		
B. Dependent Variable: Cumulative Share of Cases Using EVAR, after First Use				
Case mix lagged	-.035 [.04]	-.049* [.026]	-.036*** [.005]	-.034*** [.005]
AAA volume lagged	.0057*** [.002]	.0025** [.001]	.0004*** [.0001]	.0005*** [.0001]
AAA share of total cases lagged	.47 [.5]	.86*** [.3]	.37*** [.02]	.35*** [.02]
Years of experience	.0035 [.0025]	.0016 [.0021]	.0249*** [.0005]	.0251*** [.0005]
Board certification	-.0283 [.0387]	-.0324 [.0286]		
Fellowship	-.0584 [.0461]	-.0415 [.0310]		
C. Dependent Variable: Share of Cases Using EVAR				
Case mix lagged	-.049 [.04]	-.050* [.03]	-.040*** [.01]	-.034*** [.01]
AAA volume lagged	.0072*** [.002]	.002 [.001]	-.0017*** [.0002]	-.0015*** [.0002]
AAA share of total cases lagged	.68 [.6]	1.25*** [.3]	.65*** [.05]	.61*** [.05]
Years of experience	.0024 [.0027]	-.0026 [.0017]	.0456*** [.0010]	.0465*** [.0010]
Board certification	.0417 [.0381]	.0227 [.0294]		
Fellowship	-.0378 [.0477]	-.0358 [.0298]		
D. Dependent Variable: Used EVAR ≥ 5 Times				
Case mix lagged	-.053 [.05]	-.057 [.05]	-.02* [.01]	-.024* [.01]
AAA volume lagged	.011*** [.004]	.007** [.004]	.0008* [.0005]	.0007 [.0005]
AAA share of total cases lagged	.38 [.97]	.84 [1.0]	-.46*** [.1]	-.46*** [.1]

TABLE 4
(Continued)

Explanatory Variable	OLS	Hospital Fixed Effects	Physician Fixed Effects	Physician + Hospital Fixed Effects
Years of experience	-.0003 [.0032]	-.0049* [.0029]	.0731*** [.0016]	.0738*** [.0016]
Board certification	.0818 [.0611]	.0401 [.0538]		
Fellowship	-.0089 [.0581]	.0389 [.0498]		
Inpatient data time-varying surgeon characteristics	X	X	X	X
Inpatient data time-invariant surgeon characteristics	X	X		
Physician data time-varying surgeon characteristics	X	X	X	X
Physician data time-invariant surgeon characteristics	X	X		
R^2	.395	.7	.957	.959

Note.—Robust standard errors are in brackets. For OLS and hospital fixed-effect specs, standard errors are clustered by physician, and for models with physician fixed effects, standard errors use the Huber-White adjustment. Regressions are weighted by patient volume. Inpatient data time-varying surgeon characteristics include fee-for-service patient share and HMO patient share; inpatient data time-invariant surgeon characteristics include pretechnology cumulative case mix and pretechnology cumulative AAA volume; physician data time-varying surgeon characteristics include years in practice; and physician data time-invariant surgeon characteristics include dummies for academic medical center appointment and board certification in general surgery, vascular surgery, and/or thoracic surgery.

* $p < .1$.

** $p < .05$.

*** $p < .01$.

quantity response is particularly important in the health care setting, where administrative prices exhibit limited or no variation with respect to quality of care.³⁰

Peers possess a common knowledge base that provides a similar level of expertise in judging the quality of services provided. The repeated nature of the interactions among peers through formal referral networks is plausibly the mechanism underlying the observed responsiveness to an individual practitioner's outcomes.

The ability to track and record the performance of peer surgeons, while beneficial to patients and essential for reputation building, is costly. Some may argue that the role of physicians as agents for their patients should provide sufficient incentives to engage in this behavior. However, there are no clear financial incentives for peer physicians to do so. Under existing antikickback statutes, financial transfers are scru-

³⁰ Even the movement toward pay for performance rarely relies on patient outcomes, but rather uses process measures to inform pricing.

tinized; yet relaxing these laws is unlikely to generate incentives for efficient referrals. For example, multispecialty groups that include primary care physicians and surgical specialists provide a systematic way to bypass these laws and allow for financial transfers between physicians; however, such arrangements are not likely to provide incentives specific for tracking peer performance inside or outside the group.

To encourage physicians to engage in peer assessments, incentives must target the effort involved in tracking and recording the performance of peer surgeons. While some modern trends are likely to reduce the costs of peer assessments, such as report cards and electronic records, others are likely to increase these costs. For example, greater division of labor along the care continuum reduces the interaction among physicians.

Our conceptual framework suggests that younger (lower-volume and higher-severity case mix) physicians delay adoption of new technologies. This does not imply that surgeons use an inferior technology to show off their superior ability relative to their peers, but rather that they seek patients for whom the old technology is considered more appropriate even after the introduction of the new technology. Our empirical analysis confirms this prediction, which is counterintuitive to the beliefs often held in the medical community. The welfare implications of delays in technology adoption are generally unclear given the role of uncertainty and learning. The finding that higher-volume surgeons adopt earlier provides some indication of matching of task to talent, since these surgeons possess greater experience in managing patients targeted by the new technology.

Finally, it is important to note that our theoretical analysis does not allow for supply-side incentives that could be influencing adoption patterns as well. It is possible that manufacturers target their detailing efforts at specific surgeons. While it is likely that these surgeons would perform many AAA repairs, manufacturers are not likely to target surgeons with a lower-severity case mix.

Appendix A

From the first-order condition,

$$\beta \cdot V'(R_{t+1}) \cdot \left(B_H - B_E \cdot \frac{t_H}{t_E} \right) = - \frac{\partial u(I(H_t, R_t))}{\partial I_t} \cdot \left(1 - \frac{t_H}{t_E} \right) \cdot \bar{D}.$$

Rearranging and moving back a period, we get

$$\begin{aligned} V'(R_t) &= \frac{\partial u(I(H_{t-1}, R_{t-1}))}{\partial I_{t-1}} \cdot \frac{(t_H - t_E) \cdot \bar{D}}{\beta \cdot (B_H \cdot t_E - B_E \cdot t_H)} \\ &= u'(I_{t-1}) \cdot \frac{(t_H - t_E) \cdot \bar{D}}{\beta \cdot (B_H \cdot t_E - B_E \cdot t_H)}. \end{aligned}$$

Now, plugging into the envelope condition and defining $u'(\cdot)$ as $u'(I_t) \equiv \partial u(I_t, R_t) / \partial I_t$, we get

$$\begin{aligned} u'(I_{t-1}) \cdot \frac{(t_H - t_E) \cdot \bar{D}}{\beta \cdot (B_H \cdot t_E - B_E \cdot t_H)} &= u'(I_t) \cdot \left[\bar{D} \cdot \frac{T'(R_t)}{t_E} \right] \\ &+ \beta \cdot \left[u'(I_t) \cdot \frac{(t_H - t_E) \cdot \bar{D}}{\beta \cdot (B_H \cdot t_E - B_E \cdot t_H)} \right] \\ &\cdot \left[1 + B_E \cdot \frac{T'(R_t)}{t_E} \right]. \end{aligned}$$

Rearranging, we get

$$\begin{aligned} u'(I_{t-1}) \cdot (t_H - t_E) \cdot \bar{D} &= u'(I_t) \cdot \left[\bar{D} \cdot \frac{T'(R_t)}{t_E} \right] \cdot \beta \cdot (B_H \cdot t_E - B_E \cdot t_H) \\ &+ \beta \cdot [u'(I_t) \cdot (t_H - t_E) \cdot \bar{D}] \cdot \left[1 + B_E \cdot \frac{T'(R_t)}{t_E} \right] \end{aligned}$$

as long as $B_H \cdot t_E \neq B_E \cdot t_H$.

Distributing terms, simplifying, and advancing forward one period gives the Euler equation:

$$u'(I_t) = \beta \cdot u'(I_{t+1}) \cdot \left[1 + T'(R_{t+1}) \cdot \frac{B_H - B_E}{t_H - t_E} \right].$$

QED

Appendix B

To study whether AAA stent graft adoption was driven by a hospital-level decision, figure B1 plots the share of hospitals by the adoption share and year. The adoption share is measured as the share of surgeons within each hospital using the new technology and is divided into six mutually exclusive categories: 0 percent, 1–19 percent, 20–39 percent, 40–59 percent, 60–79 percent, and 80–100 percent.

The key observation here is that hospitals move through the adoption share categories, from the darkest band to the lightest band, in gradual fashion. Therefore, adoption of AAA stent grafts is consistent with a within-hospital phenomenon as opposed to a between-hospital phenomenon (i.e., a movement from no surgeons using the technology to all surgeons using the technology).

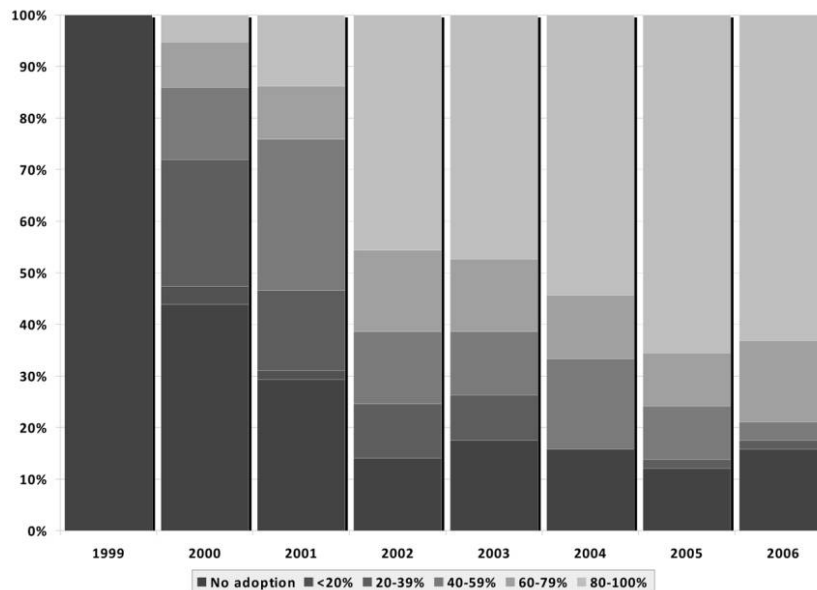


Figure B1.—Share of hospitals by share of their surgeons who have adopted EVAR

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