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The Diffusion of a Medical Innovation: Is Success in the Stars?

Mary A. Burke,* Gary M. Fournier,† and Kislaya Prasad‡

This paper relates the diffusion of the *coronary stent* to the presence of prominent or "star" physicians within a local peer group. The paper uses panel data on coronary care in Florida covering the period immediately following the 1995 Food and Drug Administration (FDA) approval of the stent, a significant improvement in coronary angioplasty. Adoption timing and utilization varied considerably across doctors between 1995 and 2001. We consider the role of asymmetric social influence among physicians based on professional status. Defining "star" status as having completed residency at a top-ranked hospital, we find that the diffusion of stents by non-stars depends positively on the number of stars practicing contemporaneously at the same hospitals, while we find no social influence in the opposite direction. The findings indicate that lack of local exposure to star physicians may slow adoption, and clustering of stars in a small number of hospitals may entail welfare costs.

JEL Classification: I10, I11, O33

1. Introduction

Traditional economic theories of technology adoption and diffusion have naturally emphasized the role of economic incentives, predicting that new technologies will be adopted based on their expected costs and benefits. More recent research in economics has considered the social conditions under which diffusion takes place, with particular concern for the process by which information about new technologies spreads across individuals and becomes salient. The latter approach does not necessarily negate the former, but it introduces the possibility that perceived benefits and costs may depend on the social environment. For example, Munshi (2004) finds a significant role for social learning in the adoption of high-yield crop varieties in India, and Huckman (2003) finds that individuals with a high level of expertise or

* Economic Research Department, Federal Reserve Bank of Boston, P.O. Box 55882, Boston, MA 02205, USA; E-mail mary.burke@bos.frb.org.

† Department of Economics, Florida State University, Tallahassee, FL 32306-2180, USA; E-mail gary.fournier@fsu.edu; corresponding author.

‡ Robert H. Smith School of Business, University of Maryland at College Park, College Park, MD 20742, USA; E-mail kprasad@rhsmith.umd.edu.

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"technological status" exert a significant influence on the technology choices of others in the same professional community. While many economists viewed Griliches' early study of hybrid corn adoption as roundly invalidating the prior sociological theories of diffusion based on social ties, more recent research suggests that such ties should not be lightly dismissed (Griliches 1957; Skinner and Staiger 2005).

With regard to medical technology adoption in particular, a number of studies identify a significant role for social interactions (see, for example, Young et al. 2003; Browman et al. 2005). Coleman, Katz, and Menzel (1966) showed that prescription of the then-new drug tetracycline occurred earlier among physicians with higher numbers of academic citations; adoption among less-cited doctors depended significantly on whether or not they interacted with more prominent peers. Schectman et al. (2003) and Bhandari et al. (2003), among others, show that treatment practices respond more strongly to in-person educational interventions and to changes in peer practices than to dissemination of practice guidelines or new clinical findings via peer-reviewed journals. Medical industry literature shows that pharmaceutical companies and medical device manufacturers target "opinion leaders" in the medical community in their marketing efforts, on the assumption that adoption by such individuals will serve as an efficient engine for more widespread adoption of the drug or device.[1] A number of studies indicate the effectiveness of such marketing efforts, for good or ill.

Despite a recent surge in interest in social interactions within economics, rigorous study of the phenomenon of "opinion leadership" in technology diffusion remains relatively scarce outside of the medical literature (see, for example, Soumerai et al. 1998; Borbas et al. 2000; Berner et al. 2003). In the case of medicine, the susceptibility of diffusion to the contingencies of social influence may entail large welfare consequences; therefore, the issue warrants further study. A rich data set on medical treatment in Florida enables us to examine the diffusion process for coronary stents. A stent is a cylindrical-mesh metal device that is inserted into the coronary artery in the process of balloon angioplasty, in order to keep the artery open after surgery. The device reduced the incidence of post-surgical coronary artery collapse, thereby reducing the need for subsequent emergency coronary bypass surgery (CABG), and reducing the incidence of restenosis (re-narrowing of the coronary artery) in the year following angioplasty. Stent use spread to a large proportion (about 90%) of angioplasty patients within a relatively brief period (from 1995 to late 2001 in the Florida data), and contributed to an increase in angioplasty usage in general. While this might be viewed as a success story (for example, compared with the relatively slow and spotty diffusion of the use of beta-blockers shown by Skinner and Staiger 2005), we observe considerable variation in the adoption and utilization rates during the diffusion period, and the eventual convergence to widespread use was not inevitable.

Defining "stars" on the basis of having completed medical residency at a hospital ranked in the top 30 nationally, and alternatively, at one ranked in the top 10, we study the influence of the number of stars working contemporaneously at the same hospital as a given non-star physician on the adoption hazard and utilization rates of non-stars. It may be that expert practitioners teach others the appropriate use of the procedure, or simply that experts, among others using a new procedure, are more likely to be imitated by their peers. Over the diffusion period, we find that the presence of stars increases the probability of adoption and utilization rates among non-stars, but we find no social influence in the opposite direction. Thus, the

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[1] An example of a company in this industry is available at http://www.leadershipinmedicine.com/news.htm.

unequal distribution of prominent physicians across hospitals leads to treatment inequalities that may entail welfare losses.

A number of recent papers have studied the properties of models with social interactions (Glaeser and Scheinkman 2001; Blume and Durlauf 2001). In the standard approach, preferences involve a penalty for departing from the average behavior of a reference group. In the case of physicians, there are justifications for an influence of average group behavior, such as when individuals seek to conform with local practice standards for fear of malpractice liability, or if productivity spillovers and social learning effects depend on average behavior. However, asymmetric influences have not been well-examined within this literature—influences we think should be particularly relevant within professional communities. Although the literature on herding and information cascades recognizes that early decisions by a small number of individuals can play a large role in determining technology choice (Bikhchandani, Hirshleifer, and Welch 1992), the order of decision-making in such models is often random. In social learning models (Conley and Udry 2001; Munshi 2004) agents are thought to be learning from each other simultaneously, and differences in the ability to learn independently are suppressed.

Professional communities tend to give rise to hierarchies based on skill and expertise, in which those at the top are emulated by others. In their classic study of the forms of social power, French and Raven (1968) identify, as one of the bases of power, expert power. Under expert power, an individual exerts influence on others because of her superior knowledge or ability. The importance of a subset of key individuals was also outlined in Rogers' study of the diffusion of innovations, following which they are often referred to as key opinion leaders (Rogers 1995). Studies in the medical literature have shown that "best practices" may not be used even when clear practice guidelines exist. The failure to adopt best practices cannot be readily attributed to ignorance of practice guidelines or results of clinical trials. Rather, some physicians argue that success of a therapy in clinical trials does not necessarily imply its success "in the real world" (Collins, Hawks, and Davis 2000). As documented by Soumerai et al. (1998), the experience of influential peers working in similar environments may, rightly or wrongly, be perceived as more relevant or convincing than evidence from clinical trials. The current study provides further evidence of asymmetric, local influences in technology adoption, and also helps to identify the characteristics of influential individuals.

2. Medical Background

The full technical name for coronary angioplasty is percutaneous transluminal coronary angioplasty, or PTCA. PTCA is one of three major classes of treatment for coronary artery disease (CAD), together with coronary artery bypass grafting (CABG) and non-invasive medical management. During PTCA, a balloon catheter is inserted through the skin in the patient's groin and threaded through to the coronary artery, where the balloon is inflated to expand the artery and restore blood flow. PTCA is far less invasive than CABG but comes with risk of complications. For example, the coronary artery can collapse immediately following the procedure, in which case emergency CABG is required. In addition, restenosis (a return of blockage of the coronary artery) can occur within a period of several months, necessitating additional intervention (either repeat PTCA or CABG) and possibly resulting in death.

A study of California discharge data estimates that in 1993, prior to the introduction of stents, about 6% of acute myocardial infarction (AMI) patients and 3.7% of non-AMI patients required emergency CABG after PTCA, while in 1996, one year after their introduction, these figures had fallen significantly, to 5.2% and 2.6%, respectively. In addition, the use of stents resulted in significant reductions in 6-month restenosis rates from 30% to 25% based on one clinical trial (Kimura et al. 1993), and from 61% to 41% in another (Agostoni et al. 2006). Study results differ in whether they find significant declines in one-year mortality rates with use of stents, however, because revascularization (i.e., repeat PTCA or CABG) reduces mortality risk from restenosis. However, revascularization rates are significantly lower when stents are used (Agostoni et al. 2006).

In 2003, a second generation of stents received Food and Drug Administration (FDA) approval in the U.S., called "drug-eluting" stents for their ability to release medications to prevent restenosis. The latter innovation further reduced restenosis rates to 8.9%, according to the larger of two clinical trials of Johnson and Johnson's CYPHER stent.[2] Over the period of our study, 1995–2001, we observe the diffusion of just the bare-metal stent. While stent outcomes may have improved during this period as a result of learning-by-doing, such improvements can be considered marginal relative to the discrete effect of the introduction of stents. Drug-eluting stents can be seen as a distinct innovation given their dramatic effects on restenosis, and so it is important that the data refer only to bare-metal stent usage.

3. Data and Empirical Specification

Data for this study were taken from patient records in the Florida hospital patient discharge database spanning the years 1994 through 2001. This standardized database records the diagnostic and procedure codes of every patient stay in all Florida hospitals, various payment and admission status fields, as well as information about the physicians who were assigned as either operating room physician or attending physician for the patient. Because coronary stents were an innovation specifically targeted at the coronary angioplasty procedure, we restrict attention to those patients over 25 years of age who received PTCA in one of 88 major medical centers around the state during the period of observation. The hospitals were chosen based on having cardiac catheterization labs, evidence of PTCA procedures performed, and continuous data for all of the physicians and quarters needed for the empirical analysis. Out of 800,709 heart patients sampled in this period, 148,174 received the angioplasty procedure.[3] These records were aggregated at various levels to obtain the rates of stent use by hospital, by surgeon, by district, and by quarter statewide, for each of the 25 quarters. Because the panel model requires lagged values for certain variables, data from 1995 were used only to obtain the lagged variable for 1996, and the models were restricted to the years 1996 to 2001.

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[2] The CYPHER is one of the two dominant drug-eluting stents in the market, the other being the Taxus stent, manufactured by Boston Scientific. The different stents release different drugs, but have been shown to have similar clinical outcomes. For more information, see the Websites http://www.fda.gov/bbs/topics/NEWS/2003/NEW00896.html and http://www.ptca.org/articles/stent.html.

[3] This compares to the statewide total of 97 hospitals who treated 1,065,768 patients admitted with principle diagnosis of AMI or atherosclerosis. A hospital was only left out of the sample if none of the physicians in our study operated there.

Table 1. Diffusion of Angioplasty and Stent Utilization, Conditional on Angioplasty, in Florida Hospitals

	Percutaneous Transluminal Coronary Angioplasty			Stents, Given Angioplasty		
Quarter	25th Percentile	75th Percentile	Mean Rate	25th Percentile	75th Percentile	Mean Rate
1995:IV	0.022	0.374	0.236	0.174	0.319	0.251
1996:I	0.038	0.368	0.239	0.250	0.426	0.334
1996:II	0.034	0.372	0.241	0.330	0.506	0.401
1996:III	0.024	0.369	0.239	0.333	0.543	0.418
1996:IV	0.053	0.371	0.248	0.423	0.569	0.487
1997:I	0.012	0.370	0.232	0.444	0.588	0.513
1997:II	0.014	0.379	0.238	0.455	0.618	0.529
1997:III	0.000	0.403	0.244	0.532	0.680	0.622
1997:IV	0.000	0.415	0.251	0.594	0.744	0.677
1998:I	0.000	0.400	0.250	0.652	0.800	0.719
1998:II	0.000	0.398	0.263	0.667	0.798	0.732
1998:III	0.000	0.418	0.269	0.708	0.855	0.774
1998:IV	0.000	0.424	0.275	0.741	0.856	0.790
1999:I	0.005	0.429	0.270	0.740	0.858	0.796
1999:II	0.011	0.447	0.290	0.777	0.883	0.819
1999:III	0.003	0.441	0.289	0.798	0.900	0.836
1999:IV	0.009	0.427	0.279	0.805	0.896	0.844
2000:I	0.016	0.432	0.278	0.812	0.905	0.856
2000:II	0.017	0.452	0.299	0.824	0.907	0.869
2000:III	0.031	0.449	0.298	0.832	0.914	0.863
2000:IV	0.059	0.433	0.289	0.830	0.925	0.877
2001:I	0.056	0.452	0.298	0.864	0.937	0.895
2001:II	0.048	0.445	0.303	0.840	0.930	0.875
2001:III	0.034	0.448	0.304	0.848	0.933	0.881
2001:IV	0.077	0.457	0.313	0.848	0.936	0.880

A broad picture of treatment patterns across hospitals is shown in Table 1. In Florida, from 1995–2001, mean PTCA rates rose slightly as a fraction of patients admitted for AMI or atherosclerosis. However, judging from the 25th to 75th percentile ranges, even at the end of the period PTCA rates vary significantly across hospitals. Regarding the use of stents among PTCA patients, initial adoption (in 1995) was limited and exhibited substantial variation across hospitals. By late 2000, however, these rates had increased dramatically, to about 88%, and cross-hospital variation had become minimal.[4]

Our hypothesis is that stars exert a strong influence on non-star physicians and influence in the opposite direction is weak or non-existent. Stars may be influenced by some of their peers (for example, other stars), but it is also possible that they have the ability to learn from external sources or personal experience to an extent that other physicians do not. If so, they may also be more likely to adopt new technologies early on. Given their expertise, they may instruct others, either directly or by example, in the proper execution and application of the procedure; such instruction may be more effective than having each individual learn from primary sources. There may also be a simple desire to mimic prominent physicians in order to identify oneself

[4] Stent usage is not universal because it entails greater risks of complications for patients with very narrow arteries and those with diabetes.

with them.[5] In this scenario, we would expect the behavior of non-star physicians working in the proximity of stars to differ from that of physicians not exposed to prominent peers, all else being equal.

Of course, we cannot directly observe which physicians in our data are considered stars by their peers. As a proxy for prominence or "star" status, we initially identify those individuals who completed residency training since 1975 in a hospital ranked in the top 30 nationally for heart surgery, a group that comprises about 12% of the physicians in our sample.[6] Residency hospitals might predict star status due to selection effects, for example, because the top hospitals are likely to select the most promising physicians. This may also occur due to treatment effects, such as when residency at a top hospital increases an individual's social esteem during her subsequent career or raises the probability of getting jobs that facilitate professional influence. Top hospitals are also more likely to be associated with early adoption of new technologies (Hashimoto et al. 2006).

However, our data show no systematic tendency of "stars" to adopt earlier than others, nor a tendency for stars to have higher utilization rates than others. Despite this observation, we hypothesize that early adoption by non-stars is less likely to raise subsequent adoption rates (by peers of any rank) than is early adoption by stars. Thus, our definition of stars need only identify relatively influential individuals and not necessarily those most likely to be early adopters or more frequent users of stents. Evidence of this type of asymmetric influence in a different professional sphere is given by Podolny and Stuart (1995). They find that, among patent-holders, the higher-status individuals (defined on the basis of previous professional contributions) held the patents that were most likely to inspire subsequent innovations.

The classification of physicians as stars or non-stars is predetermined and constant over all time periods in the model, but the extent of star influence can vary across (non-star) physicians and over time. For a given non-star physician and a given time period, the "star" variable is the total number of stars treating patients (regardless of stent usage) at any of the hospitals at which the given physician practiced during the given quarter.[7] In the lexicon of social interactions, this is an example of a "contextual" or "exogenous" peer effect, since the peer variable is a feature of the peer group's fixed characteristics rather than of its behavior. Since we find no systematic association between star status and behavior (in simple models of adoption and utilization ignoring social influences), the number of star peers is not also proxying for the stent rate among the entire peer group (stars and non-stars combined). It may proxy for the number of stenting procedures performed by stars, since the latter can be expected to increase with the number of stars. In this way, the model does a better job of capturing the influence of specific individuals than if there were simply a social multiplier on general stent use among peers.

Because physicians are not assigned to hospitals at random, we must control for the possibility that the number of star peers for a given physician is correlated with unobserved

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[5] An alternative possibility is that influential individuals are heavily pushed by medical manufacturers to adopt technologies early on. The welfare consequences are likely to be different in this case. To contrast the stent innovation with computer adoption, see Goolsbee and Klenow (2002), who consider an example of "status-based imitation" where adoption may occur without subsequent use.

[6] Rankings are based on *U.S. News and World* report survey, July 18, 2005. Rankings are not irrefutable, but we find that the ones we could track (university-affiliated teaching hospitals) also ranked in the top tier based on NIH grant activity.

[7] The number of stars is the most reliable measure of contact we are able to infer with our data; we cannot ascertain how contacts with star peers vary in terms of their degree of influence in social interaction.

treatment preferences. For example, non-stars with a propensity for early adoption (or eventual high stent utilization) may seek out the types of hospitals with a relatively high number of star doctors. Given the panel data and consistent physician identifiers, we can control for the fixed effects of unobserved physician factors. We cannot control for correlated movements over time in unobserved treatment tendencies and the number of star peers. However, we find it unlikely that individual physicians can readily adjust the number of star peers from year to year in response to changes in treatment propensities. Controls for other sources of spurious star effects are discussed later.

We estimate two models, representing two stages of choice. The first equation represents the hazard of discrete stent adoption by all physicians, which we define as the event that the doctor has used stents three times. The second equation represents the choice of utilization rates by physicians, both non-stars and stars, subsequent to having adopted and so includes only those physicians that have adopted as of the given quarter. The adoption hazard follows a complementary log-log hazard model. Because our data are collected quarterly and the exact dates of surgery are unavailable, the adoption hazard follows the complementary log-log model if we assume that the adoption events are generated by Cox's proportional hazards model (Allison 1999). The model is

$$\log(-\log(1 - p_{rt})) = \alpha_h + c_t + \gamma S_{rt} + \mu NS_{rt} + \beta X_{rt} + \delta V_{r,t-1}. \quad (1)$$

The model in Equation 1 implies that the probability of adoption at a given time depends on fixed properties of the hospital(s) where the physician practices (one dummy, α_h, for each relevant hospital is included), the current calendar date c_t (a specific quarter), the average age and race of the doctor's current patients, X_{rt}, the physician's lagged number of angioplasty procedures, $V_{r,t\text{-}1}$, the current number of non-star peers, NS_{rt}, and the current number of star peers, S_{rt}.

We expect the coefficients on each of the last two variables to be positive. However, it is consistent with our main hypothesis that the effects are asymmetrical; stars should have strong influence on non-stars but not the reverse. Constraints on the effects of NS_{rt} and S_{rt} can be tested to see whether the effects are different for star physicians, grp_1, and non-stars, grp_2.

$$\log[-\log(1 - p_{rt})] = \alpha_h + c_t + \gamma * grp_2 * S_{rt} + \mu * grp_1 * NS_{rt} + \beta X_{rt} + \delta V_{r,t-1}. \quad (2)$$

The quarterly fixed effects in Equation 2 capture common state-level influences, such as global learning externalities, global information dissemination, or global contagion effects. These time dummies may proxy for the influence of the lagged statewide adoption rate, which enters diffusion models with global interactions, but the time effects are more general and allow for non-linear trends.

The second equation estimates stent utilization rates (for angioplasty patients) by non-star physicians, conditional on adoption. The second equation is subject to censoring because we do not observe stent rates per patient until after the surgeon has adopted, and only include those who have adopted as of each quarter. However, we observe no reversals of adoption (for example, a physician who adopted previously and later performs less than three stent procedures). Thus, the model is "sequentially exogenous," in the sense that the adoption decision is predetermined when the utilization rate is observed.[8] Therefore, censoring correction

[8] For alternative examples and discussion, see chapter 11 in Wooldridge (2002) and Papke (1994).

is not necessary; however, the equation represents utilization conditional on adoption and not the global utilization equation. The model is as follows

$$u_{rt} = p_r + \alpha_h + c_t + \gamma_r S_{rt} + \beta X_{rt} + \delta V_{r,t-1} + \varepsilon_{rt}. \tag{3}$$

In Equation 3, the variables S_{rt}, X_{rt}, V_{rt}, α_h, and c_t are the same as in the adoption equation. The dependent variable is the number of instances of stent usage per thousand angioplasties performed by the physician in the given period. The p_r represent individual physician fixed effects. We can establish the reverse relationship by analyzing the utilization rates of star physicians, and testing whether the number of non-stars, NS_{st}, has a significant influence:

$$u_{st} = p_s + \alpha_h + c_t + \gamma_s NS_{st} + \beta X_{st} + \delta V_{s,t-1} + \varepsilon_{st}. \tag{4}$$

When all observations are pooled for star physicians, grp_1, and non-stars, grp_2, there is some efficiency gain, and the equation becomes

$$u_{it} = p_i + \alpha_h + c_t + \gamma_r grp_2 * S_{rt} + \gamma_s grp_1 * NS_{st} + \beta X_{it} + \delta V_{i,t-1} + \varepsilon_{it}. \tag{5}$$

The group restrictions in Equation 5 remove the effects of S_{rt} on star physicians, as well as the effects of NS_{st} on non-stars. Estimating Equations 3 and 4 separately, or in a pooled regression, allows the number of star peers to influence stars as well as non-stars. However, there may be reasons to expect less peer influence on stars, perhaps due to superior ability to integrate the results of research. One can test these restrictions to see if stars exert a greater independence.

4. Results

The results of our empirical models are provided in this section. To obtain the sample, summarized in Table 2, we compiled the hospital surgery activities of surgeons for as many quarters as possible during 1995-2001. If a physician performed surgery at multiple hospitals, variables were aggregated for the physician across all patients and hospitals.[9] Not every surgeon could be evaluated from the available data; for instance, the sample is subject to observing a physician for at least four consecutive quarters.[10] Moreover, it was necessary to match biographical information from the Florida Department of Health to determine their residency and graduation years. The final sample includes approximately 239–280 physicians in each quarter.

Recalling Table 1, we note that the diffusion of stents became convergent and its usage widespread throughout all hospitals in the final two years. Thus, if we believe the strength of influence will be confined mainly to the early periods when adoption has not fully completed,

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9 Of all surgeons in our sample, 54% operated at only one hospital, 33% at two hospitals, 10% at three hospitals, 2% at four hospitals, and 1% at five to seven hospitals. We have not attempted to study changes in practice style by the doctor at different hospitals.

10 We are using fixed effects for physicians in the model, so it is necessary to observe individuals over time. The results reported below are not changed qualitatively if we relax the criteria to only three consecutive quarters. In total, we are studying 21% of all physicians who performed at least one angioplasty in the state; these individuals account for 58% of all these procedures.

Table 2. Summary Statistics

Variable	Mean	Standard Deviation	Minimum	Maximum
Adoption model (n = 373 observations)				
Lag physician volume	11.855	13.142	1.000	92.000
Physicians in grp1, ("star")	0.118	0.323	0.000	1.000
Mean patient age	64.336	6.546	39.000	89.000
Proportion patient race				
Black	0.070	0.150	0.000	1.000
Hispanic	0.083	0.207	0.000	1.000
Other	0.038	0.103	0.000	1.000
Stars encountered	1.796	1.832	0.000	10.000
Non-stars encountered	33.635	22.100	2.000	175.000
Physicians in grp1, ("star")*(non-stars encountered)	3.542	11.933	0.000	82.000
Physicians in grp2, ("non-star")*(stars encountered)	1.453	1.745	0.000	10.000
Utilization model (n = 6137 observations)				
Lag physician volume	22.876	16.649	1.000	134.000
Mean patient age	64.704	4.475	30.000	83.500
Proportion patient race				
Black	0.048	0.076	0.000	0.833
Hispanic	0.085	0.188	0.000	1.000
Other	0.046	0.082	0.000	1.000
Star variables using top 30–ranking criterion (n = 6137 observations)				
Graduation year	1984.340	7.135	1961	1998
Physicians in grp1 ("star")	0.135	0.341	0.000	1.000
Stars encountered	2.418	2.625	0.000	14.000
Non-stars encountered	40.441	31.380	2.000	215.000
Physicians in grp1 ("star")*(non-stars encountered)	5.233	17.357	0.000	165.000
Physicians in grp2 ("non-star")*(stars encountered)	1.951	2.523	0.000	13.0
Star variables using top 10–ranking criterion (n = 6137 observations)				
Graduation year	1984.340	7.135	1961	1998
Physicians in grp1 ("star")	0.048	0.214	0.000	1.000
Stars encountered	0.743	1.137	0.000	6.000
Non-stars encountered	42.117	33.357	2.000	216.000
Physicians in grp1 ("star")*(non-stars encountered)	1.487	7.650	0.000	100.000
Physicians in grp2 ("non-star")*(stars encountered)	0.637	1.067	0.000	6.000

the advantage of a shorter interval is to eliminate the 'flat of the curve.' In Table 3, the data report the rapid adoption that occurred in this state during the first eight quarters. For this reason, the hazard model is estimated over the first two years, 1996 and 1997.

A further breakdown of the effect of social interaction is illustrated in the next two tables. Table 4 cross-tabulates the adoption rates of star and non-star physicians in the first two years, based on the number of star physicians the doctor encounters in practice. We defined physicians to be stars based on an exogenous criterion, the quality of residency training. This is meant to identify relatively influential individuals. There is no presumption that the stars would

Table 3. Number of Doctors and Stent Rates by Quarter

Quarter	Physicians	Physicians Adopting (%)	Leaving Sample	Entering Sample	Stents	Utilization Rates
1995:IV	239	123 (51.464)	0	0	1031	0.260
1996:I	248	170 (68.548)	0	9	1679	0.336
1996:II	249	205 (82.329)	0	1	1888	0.412
1996:III	257	218 (84.825)	0	8	1667	0.417
1996:IV	259	228 (88.031)	0	2	2116	0.476
1997:I	269	251 (93.309)	3	13	2976	0.516
1997:II	270	260 (96.296)	0	1	2996	0.541
1997:III	274	268 (97.810)	0	4	3301	0.626
1997:IV	276	271 (98.188)	0	2	4079	0.683

necessarily be early adopters relative to non-stars. Adoption rates for all types are at or near 1.0 by the end of the period. Interestingly, among non-star physicians who are not interacting with star peers, the adoption rates throughout the period are somewhat lower than those who have five or more such peers. The stent rate, or utilization, diffused more slowly than the adoption event, continuing to increase throughout much of our sample period. Table 5 shows that the use of stents by star physicians is not much different than non-stars who work at the same hospitals throughout the six-year period. But the utilization of non-stars who lack interaction with the star physicians is slightly lower. We do not require that the star physicians are the individuals who are the first to adopt. It could be that stars have superior ability to integrate the results of research studies and engage in informal communications. Our hypothesis is simply that innovation will spread faster among non-stars in places where influential physicians operate. Whether these simple statistics are valid or not, they suggest the kind of effect that more controlled, panel models are intended to examine.

Table 6 reports the estimation results for the hazard model. Two versions are reported. The main results show that the estimated hazard rate is rising over time, reflecting global diffusion statewide, and is higher when the doctor has a larger patient volume, holding patient mix constant. As for our focal variable, in both models, the number of stars is found to be (marginally) insignificant, with the first p-value, 0.12, not too far from significant, while in the

Table 4. Stent Adoption by Type of Physician and Social Interaction with Stars

	No Stars Encountered	1–2 Stars Encountered		3–4 Stars Encountered		5 or More Stars Encountered	
Quarter	Non-Star Physician Adoption Rate	Star Physician Adoption Rate	Non-Star Physician Adoption Rate	Star Physician Adoption Rate	Non-Star Physician Adoption Rate	Star Physician Adoption Rate	Non-Star Physician Adoption Rate
1995:IV	0.452	0.650	0.500	0.600	0.630	0.667	0.742
1996:I	0.704	0.789	0.712	0.750	0.697	0.571	0.890
1996:II	0.884	0.850	0.804	0.833	0.827	0.750	0.923
1996:III	0.857	0.850	0.856	0.857	0.897	0.875	0.973
1996:IV	0.872	0.870	0.881	0.800	0.990	1.000	0.943
1997:I	0.966	0.900	0.912	0.857	0.963	1.000	0.982
1997:II	0.931	0.952	0.971	1.000	0.978	1.000	0.970
1997:III	0.985	1.000	0.981	1.000	0.952	1.000	0.986
1997:IV	0.960	1.000	0.980	1.000	0.950	1.000	0.983

Table 5. Social Interaction and Stent Utilization by Physicians

Quarter	Stars	Co-Located Non-Stars	Non-Stars Without Star Contact
1995:IV	0.262	0.270	0.225
1996:I	0.341	0.359	0.319
1996:II	0.424	0.439	0.361
1996:III	0.456	0.446	0.392
1996:IV	0.540	0.501	0.470
1997:I	0.543	0.513	0.514
1997:II	0.519	0.555	0.541
1997:III	0.632	0.618	0.625
1997:IV	0.702	0.686	0.660
1998:I	0.786	0.765	0.716
1998:II	0.744	0.766	0.746
1998:III	0.808	0.814	0.774
1998:IV	0.818	0.811	0.810
1999:I	0.843	0.823	0.768
1999:II	0.843	0.851	0.822
1999:III	0.850	0.842	0.792
1999:IV	0.880	0.868	0.806
2000:I	0.845	0.876	0.847
2000:II	0.852	0.881	0.858
2000:III	0.864	0.867	0.845
2000:IV	0.889	0.895	0.863
2001:I	0.867	0.898	0.869
2001:II	0.858	0.886	0.866
2001:III	0.883	0.882	0.880
2001:IV	0.896	0.896	0.875

constrained model, the second, 0.09, is significant at $\alpha = 0.10$. The marginal effects estimates indicate a larger effect of the number of stars than of the number of non-stars, which is consistent with our expectations about the direction of influence.

The utilization models, reported next in Table 7, are least-squares panel regressions testing the alternative influence of the number of stars in a pooled sample of ($n = 5311$) non-star physician/quarters, and ($n = 826$) star physician/quarters. The results show that the model has excellent explanatory power and controls for a range of physician-specific and hospital-specific variations in stent use. For these samples, both effects are statistically significant, although only at $\alpha = 0.10$. Between the two groups, the magnitudes of the estimated effects suggest that, compared to the number of stars encountered, the non-stars exert much weaker and negative effect, suggesting an asymmetric effect between the two groups. One can interpret the "star" effect by supposing a hypothetical patient with mean characteristics who receives angioplasty from a physician getting no contact with star physicians. For this patient, if the surgeon had instead received the sample average number of star encounters, the predicted utilization rate would be 1.24% higher. The percentage effect would be higher in the earliest quarters, when stenting was at a low overall rate.[11]

[11] Additional variables were added to test restrictions on the peer effects in the model. Grp1*(Number of stars encountered) and Grp2*(Number of non-stars encountered) were added to determine, for example, if star peers have significant influence on each other. These variables have negligible explanatory power in the model.

Table 6. Estimation Results: Complementary log-log Hazard Function for Stent Adoption

	Model 1			Model 2		
Variable	Marginal Effect	Standard Error	*p*-Value	Marginal Effect	Standard Error	*p*-Value
Lag physician volume	0.007**	0.002	0.002	0.006**	0.002	0.002
"Star" physician	−0.011	0.088	0.902	−0.061	0.148	0.681
Mean patient age	0.002	0.005	0.657	0.002*	0.005	0.654
Proportion patient race						
Black	−0.486*	0.251	0.053	−0.498**	0.239	0.037
Hispanic	−0.045	0.153	0.767	−0.060	0.144	0.675
Other	−0.133	0.301	0.660	−0.138	0.299	0.644
Stars encountered	0.129	0.083	0.121			
Non-stars encountered	−0.004	0.006	0.448			
Grp2*(stars encountered)				0.110*	0.066	0.095
Grp1*(non-stars encountered)				0.012	0.008	0.128
Time period						
1996:II	0.259**	0.094	0.006	0.265**	0.096	0.006
1996:III	0.162	0.152	0.289	0.122	0.134	0.365
1996:IV	0.165	0.161	0.306	0.126	0.143	0.380
1997:I	0.624**	0.200	0.002	0.503**	0.181	0.005
1997:II	0.776**	0.050	<0.001	0.778**	0.053	<0.001
1997:III	0.769**	0.050	<0.001	0.766**	0.062	<0.001
1997:IV	0.715**	0.187	<0.001	0.720**	0.182	<0.001

The model includes fixed effects for hospitals, not reported here.
* Significance level of $\alpha = 0.10$.
** Significance level of $\alpha = 0.05$.

How one selects the appropriate threshold ranking to identify hospitals where residency training conveys real prestige is arbitrary, and the rankings themselves may not convey the correct measure of prestige. Nevertheless, it is worth reporting that the results on the effects of stars become more significant and larger in magnitude in both the hazard model and the utilization panel when "stars" are defined more narrowly, based on residency training at top-10-ranked hospitals rather than at top-30-ranked hospitals. These results are reported in summary form in Table 8. The results are highly significant in the constrained version of the model from Equations 2 and 5.

One may conclude, while noting that the significance level of the effect is below $\alpha = 0.05$ in some specifications (Table 7), in others (Table 8) the effect is highly significant. Thus, key agents who are leaders in the industry may play a small role in the transmission of technology and serve to influence the adoption by others. Note that stars have a direct and contemporaneous effect on their peers. The mechanism does not require that the outcome or effects of adoption be observed with a lag. Instead, non-stars reliably use star adoptions or utilization as a proxy for determining what the better techniques are. Once the stars have decided, there may be no gains from waiting any further.

Some limitations of our results should be mentioned. The exact channels of influence that operate among physicians are unknown, and more research into the nature of physician influence is warranted. We assume that influence is limited to physicians who practice at the same hospitals. However, influence could be wielded more broadly throughout a community or

Table 7. Panel Regression on Physician-Level Stent Utilization

	Model 1			Model 2		
Variable	Coefficient	Robust Standard Error	p-Value	Coefficient	Robust Standard Error	p-Value
Lag physician volume	0.491**	0.171	0.004	0.492**	0.171	0.004
Mean patient age	−2.196**	0.744	0.003	−2.202**	0.746	0.003
Proportion patient race						
Black	−68.374*	40.099	0.088	−68.428*	40.076	0.088
Hispanic	−60.236	42.300	0.154	−59.597	42.271	0.159
Other	37.021	38.922	0.342	37.098	38.839	0.340
Number of stars encountered	5.772*	3.036	0.057			
Number of non-stars encountered	−0.182	0.247	0.460			
Grp2*(stars encountered)				5.128*	3.053	0.093
Grp1*(non-stars encountered)				−0.157	0.331	0.63
Time Period						
1996:II	−67.217**	17.977	<0.001	−67.358**	17.970	<0.001
1996:III	−1.052	18.357	0.954	−1.748	18.334	0.924
1996:IV	47.915**	17.459	0.006	47.257**	17.513	0.007
1997:I	88.167**	17.075	<0.001	85.223**	16.717	<0.001
1997:II	98.844**	16.503	<0.001	98.757**	16.513	<0.001
1997:III	180.242**	16.046	<0.001	180.188**	16.039	<0.001
1997:IV	233.156**	15.684	<0.001	233.856**	15.663	<0.001
1998:I	288.701**	16.473	<0.001	285.821**	15.993	<0.001
1998:II	98.844**	16.503	<0.001	283.460**	15.107	<0.001
1998:III	180.242**	16.046	<0.001	326.295**	15.685	<0.001
1998:IV	233.156**	15.684	<0.001	352.143**	14.979	<0.001
1999:I	359.074**	15.364	<0.001	356.494**	14.835	<0.001
1999:II	379.814**	14.896	<0.001	379.505**	14.859	<0.001
1999:III	394.689**	15.158	<0.001	394.601**	15.125	<0.001
1999:IV	401.860**	15.556	<0.001	401.593**	15.509	<0.001
2000:I	414.814**	15.438	<0.001	412.240**	14.794	<0.001
2000:II	416.373**	14.538	<0.001	416.559**	14.500	<0.001
2000:III	404.502**	14.863	<0.001	404.051**	14.815	<0.001
2000:IV	422.976**	14.868	<0.001	422.421**	14.805	<0.001
2001:I	437.367**	16.014	<0.001	433.800**	14.944	<0.001
2001:II	421.655**	15.150	<0.001	420.926**	15.065	<0.001
2001:III	436.272**	15.080	<0.001	435.185**	14.966	<0.001
2001:IV	449.365**	15.448	<0.001	448.618**	15.409	<0.001
Intercept	560.866**	51.914	<0.001	564.705**	51.846	<0.001

The model includes fixed effects for hospitals and physicians, not reported here.
* Significance level of $\alpha = 0.10$.
** Significance level of $\alpha = 0.05$.

state via other forms of communication, such as professional meetings and publications. Moreover, a surgeon with recognized celebrity in her home hospitals may not be recognized as such were she to move to a different locale. In addition, while the fixed effects for physicians and for hospitals help to control for endogeneity in the number of star peers, residual

Table 8. Results with Stars Identified by Top-10 Ranking of Residency Hospital

	Model 1				Model 2			
	Marginal Effects	Coefficient	Robust Standard Error	*p*-Value	Marginal Effects	Coefficient	Robust Standard Error	*p*-Value
Adoption equation								
Number of stars encountered	0.702		0.464	0.130				
Number of non-stars encountered	−0.024		0.027	0.382				
Grp2*(stars encountered)					0.865**		0.425	0.042
Grp1*(non-stars encountered)					−0.012		0.048	0.800
Utilization equation								
Number of stars encountered		15.553**	4.455	<0.001				
Number of non-stars encountered		−0.192	0.246	0.435				
Grp2*(stars encountered)						12.990**	4.542	0.004
Grp1*(non-stars encountered)						0.777	0.691	0.261

The complete models are specified as in Tables 6 and 7.
* Significance level of $\alpha = 0.10$.
** Significance level of $\alpha = 0.05$.

correlations between the stars variable and unobserved, time-varying factors are possible. For example, if physicians publish journal articles frequently, star status could be changing over time. Finally, if hospitals implement updated practice guidelines for stent usage at irregular intervals, fixed effects for hospitals are not sufficient. We know of no data set that tracks the use of practice guidelines at the hospital level for this state, but there were two sets of national guidelines issued, one before and one at the end of our study period (Smith et al. 2001). To the extent that the national standards carry the greatest influence, it would appear that no major changes in guidelines occurred during the interim.

5. Conclusion

The claim that physicians are subject to social influences is probably uncontroversial. The claim that such influences may significantly affect the timing and extent of technology adoption is probably not. However, previous studies have identified measures of physician status that are associated with an influence on treatment and technology choices within physician peer groups. One such measure uses the number of citations to a physician's published research papers. Lacking ready access to this information, and recognizing that influential practitioners may not engage in research, we define star status on the basis of residency hospital affiliation. While admittedly simple, this definition bears a plausible relation to subsequent professional status given the competitive nature of residency selection. It has the added advantage of not relying on treatment volumes or early adoption propensities (either of which might be plausible signs of status), each of which is more likely to lead to spurious findings of influence. The panel data permit controls for fixed physician effects, controls which should alleviate endogeneity concerns regarding the "star peers" variable. Controls for correlated effects at the hospital level and at higher levels of aggregation further assist identification of peer influence.

Our results are noteworthy for suggesting an asymmetry of influence between peers of different status. Even though we find no significant difference in the adoption and utilization propensities of our stars and non-stars, we find that adoption (utilization) by high-status doctors is more likely, albeit at only the 10% level of significance in some specifications, to spur additional adoption (utilization) among peers than is adoption by the "rank and file." Due to the nature of the diffusion process, our results depend on which time interval we observe. We are not surprised to find that star effects are strongest in the early stages of the process, when there is more variation to be explained. Although the eventual diffusion of stent use was widespread and roughly uniform, the diffusion paths prior to saturation varied considerably across physicians, hospitals, and regions. While it is difficult to determine the efficiency properties of these paths, given that optimal stent rates during the period would have varied with a number of unobservable factors, our results suggest that an unequal distribution of high-status physicians can lead to unequal diffusion rates and variation in adoption timing, which may imply welfare costs for some patients.

Our study suggests some questions for further investigation. First, what additional factors characterize opinion leaders in medicine? A study of diffusion of other procedures, together with additional data on physicians, should give us a more complete picture. In addition, we should seek to identify the characteristics of those who are *influenced* to adopt an innovation, the characteristics of hospitals that bear on the nature of communication among physicians, as well as the marketing practices of device manufacturers (or pharmaceutical companies, etc.). Collins, Hawks, and Davis (2000) assert that "health care organizations can rapidly spread 'better practices' to their practicing physicians by understanding the social and communication networks that are naturally developed by those practitioners." After describing a number of studies of the effect of opinion leaders, they go on to suggest that facilitating communication between opinion leaders and networks will lead to improved outcomes. When possible improvements in patient outcomes are taken into consideration, the study of social effects in medical practice takes on a certain urgency.

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