Volume Title: The Changing Hospital Industry: Comparing For-Profit and Not-for-Profit Institutions

Volume Author/Editor: David M. Cutler, editor

Volume Publisher: University of Chicago Press

Volume ISBN: 0-226-13219-6

Volume URL: http://www.nber.org/books/cutl00-1

Publication Date: January 2000

Chapter Title: The Adoption and Impact of Advanced Emergency Response Services

Chapter Author: Susan Athey, Scott Stern

Chapter URL: http://www.nber.org/chapters/c6762

Chapter pages in book: (p. 113 - 168)

4

The Adoption and Impact of Advanced Emergency Response Services

Susan Athey and Scott Stern

4.1 Introduction

Emergency response services, provided through 911 calling and ambulance services, serve as the first line of contact between patients suffering from emergency conditions and the local health care infrastructure. Together with the emergency rooms in hospitals, emergency response services play an important role in the health care outcomes for a number of emergency indications. For example, in the case of out-of-hospital cardiac arrest, the time lapse between collapse and the initiation of cardiopulmonary resuscitation (CPR) and defibrillation is claimed to be an important determinant of the probability of survival.[1] In addition, the emergency response system plays a critical role in selecting which hospital receives each emergency patient, where hospitals may differ in their quality and in

Susan Athey is the Castle Krob Career Development Associate Professor in the Department of Economics, Massachusetts Institute of Technology, and a faculty research fellow of the National Bureau of Economic Research. Scott Stern is assistant professor at the Sloan School of Management, Massachusetts Institute of Technology, and a faculty research fellow of the National Bureau of Economic Research.

The authors are grateful to David Cutler, Catherine Wolfram, Karen Norberg, and conference participants for insightful discussions. John Kim, Irena Asmundson, Chris Bae, David Hellmuth, and Andres Nanneti provided exceptional research assistance. The authors are also grateful to the Pennsylvania Department of Health, and in particular Dr. Kum Ham, as well as the National Emergency Number Association, for providing the data, and to the numerous emergency response professionals who graciously provided their time and expertise. Generous financial support was provided by the Sloan School of Management at MIT and NSF grant SBR-9631760 (Athey).

1. The literature on this topic is large, but several relevant studies include Gibson (1977); Hoffer (1979); Siler (1975); Cummins et al. (1991); Bonnin, Pepe, and Clark (1993); Fischer, Fischer, and Schuttler (1997); Larsen et al. (1993); Tresch, Thakur, and Hoffman (1989); and Weston, Wilson, and Jones (1997).

the technologies available for emergency care. The patient benefits from emergency response services thus arise not only from the direct provision of medical and transportation services but also through the system's role in allocating patients to the hospital facilities that are most appropriate for their particular medical condition. Furthermore, emergency response systems may have indirect effects on patients through their influence on the choices made by hospitals. Emergency response systems affect the incentives of hospitals to adopt certain technologies, such as gaining "trauma center" certification and introducing capabilities for the provision of cardiac care, since these choices can potentially influence the allocation of emergency patients to hospitals.

There exists wide variation across communities within the United States in terms of the level of care provided through the emergency service system. For example, 911 services are publicly funded and are almost always operated by local government agencies such as police or fire departments. At one extreme, some communities have invested in "Enhanced 911" (E911) systems, which link digital information about the source of the call with a detailed address database maintained by the 911 center. The call takers see each caller's address and location on a computer screen almost instantaneously when the call is received. Even more advanced alternatives are available, including computer-aided ambulance dispatching. At the other extreme, there are many communities that have not invested even in a "Basic 911" capability. In these environments, individuals attempting to contact the local medical emergency infrastructure must locate and dial a seven-digit number. When the call is received, the call taker manually searches for and contacts the ambulance that is closest to the emergency and has the appropriate equipment. Likewise, we see substantial heterogeneity in the availability of in-hospital emergency services across communities. Although the American Heart Association has advocated the adoption of Enhanced 911 as the first step in a "chain of survival" for cardiac incidents (Cummins et al. 1991), there has been little systematic evidence presented about the benefits of 911 services.[2]

The principal aim of this paper is to evaluate the determinants and implications of differences in the prehospital and in-hospital emergency services adopted in a given community. To accomplish this goal, we evaluate the incentives to adopt emergency response systems and in-hospital technology, as well as the productivity gains from these investments. We focus in particular on the productivity and adoption of Basic and Enhanced 911 services, services that entail investments in information technology and telecommunications equipment.

2. For an exception, see Joslyn, Pomrehn, and Brown (1993), who find in a sample of 1,753 Iowa patients that 911 reduces response time, time to CPR, and time to defibrillation, as well as mortality. This study has a limited number of county-level covariates, however, leaving open issues of unobserved heterogeneity between counties.

As a service enabled by investment in information technology, emergency response systems belong to the substantial portion of the economy that has defied accurate productivity measurement (Griliches 1994; Bresnahan and Gordon 1997). For most services (including emergency response), it is difficult to measure quality. Each consumer's valuation can depend on several factors that are difficult to observe, such as timeliness and the location of service delivery as well as on the extent to which the product is customized to the individual. In the case of 911 services, however, we are able to address some of these challenges using a unique combination of data sources. The primary database is composed of a set of ambulance calls responding to reported cardiac incidents in Pennsylvania in 1995. These ambulance records have been linked with hospital billing records, hospital characteristics, and data about the level of 911 technology available in the county in which the call took place. We use this data to document how 911 is related to the benefits provided by the emergency response system, including its relationship to lower response times, more appropriate allocation of patients to hospitals, and reduced mortality of cardiac patients.

Our analysis focuses on relatively simple, reduced-form procedures. We begin by exploring the sources of heterogeneity in the allocation of 911 services to different localities. We find that 911 is allocated not only according to factors that might increase their technical efficiency (such as the number of residents per county) but also according to a county's political orientation. In particular, communities with more conservative voting patterns are less likely to adopt advanced 911 systems. Although we do not perform a formal cost-benefit analysis, these results suggest that public policies concerning 911 systems can potentially increase the efficiency of the diffusion process. For example, some of the barriers to adoption include the lack of incentives and information faced by county government officials, problems that could potentially be remedied at relatively low cost.

We then turn to analyze the productivity benefits from adopting Basic and Enhanced 911 systems, taking the patient as the unit of the analysis. We begin by studying the effects of the county-level 911 system on the time it takes to respond to cardiac emergencies and transport the patient to the hospital, factors that are an important component of the quality of emergency medical services. The detailed nature of the data set allows us to control for a variety of patient characteristics, as well as for features of the county, such as the hospital infrastructure and demographic characteristics.

We show that an ambulance arrives at the scene of a cardiac emergency 5 percent faster in counties with Enhanced 911 as opposed to no 911 or Basic 911. Even larger gains are measured when we restrict our sample solely to those counties that changed their level of 911 technology during our sample period. Moreover, patients are transported from the scene of an incident to the hospital approximately 10 percent faster in counties with Enhanced 911 as opposed to lower levels of 911.

Our findings regarding the relationship between 911 and mortality are more subtle. First, we are unable to establish a direct reduced-form statistical relationship between the level of 911 in a given county and patient mortality. Of course, this may be due to the fact that the overall mortality rate is relatively low (approximately 7 percent) and only a small portion of our sample resides in counties with no 911 technology (approximately 20 percent), making it difficult to infer the impact of the technology level on the mortality rate. However, our analysis of the impact of 911 on response time suggests an alternative strategy: We use the adoption of 911 as an instrument for an individual's response time in the patient mortality regressions. In particular, we show that 911 technology affects response time, and we can assume that 911 adoption is unrelated to the severity of a particular patient. Our preliminary instrumental variables analysis of the effect of response time on mortality finds that shorter response times do indeed reduce mortality. While this analysis is still exploratory, we believe that the use of county-level infrastructure as an instrument for individual-level services is a potentially fruitful approach for further exploration.

Beyond its direct effects on response time and mortality, a second role of the emergency response system is to allocate patients to hospitals. From a hospital's perspective, the emergency response system affects both the size and characteristics of its pool of emergency patients; the sensitivity of the allocation process to the hospital characteristics will also interact with the incentives of a hospital to adopt certain technologies. We thus take several preliminary steps toward exploring these effects.

Our first result about allocation is that patient severity affects the allocation of patients to high-technology hospitals. Our results about allocation have implications for our ability to draw inferences about the benefits of hospital technology through reduced-form analyses of the direct effect of technology on patient outcomes. This issue has been recognized by several authors, such as McClellan and Newhouse (1997), who argue that patient allocation to hospitals with different technologies is endogenous and so must be treated with an instrumental variables approach. Consistent with this view, our estimates provide *direct* evidence about the relationship between patient severity and allocation.

In addition, we document that in Pennsylvania, many patients reside in counties that do not include a hospital with certain high-level cardiac-specific technologies (such as a cardiac catheterization laboratory); as a consequence, these patients are not treated by hospitals with high-level cardiac technology in response to a cardiac emergency. It is interesting to observe that, in contrast to the general population, nearly all of the cardiac patients in our sample have some form of insurance (almost 99 percent). Instead, it seems to be the availability of medical technology in nearby hospitals that most significantly limits the access of patients to high levels of cardiac care in emergency situations.

Among the patients who do have access to high levels of cardiac care technology, we show that the allocation of patients to hospitals with cardiac catheterization laboratories depends on the presence of 911 services, where counties with higher levels of 911 technology are more likely to allocate patients to hospitals with higher levels of cardiac care technology. This can affect the incentives of hospitals to invest in high levels of technology. While these incentives can potentially lead to increased investment in technology by hospitals, we do not see strong evidence of strategic complementarity between 911 and hospital technology in our national sample. Despite the fact that the level of in-hospital emergency technology is positively correlated with the level of 911 technology at the national level, most of that positive interrelationship is accounted for by the fact that both in-hospital and prehospital care respond positively to the population and income of a county.

We further explore the salience of hospital incentives to adopt advanced technologies through a preliminary analysis of the determinants of a hospital's share of ambulance-transported cardiac patients in a given county. We find evidence that a hospital's "market share" is sensitive both to its overall level of emergency room technology as well as its level of cardiac-specific technology. In addition, increases in the level of technology by rival hospitals (other hospitals in the same county) have a negative impact on hospital market share.

The remainder of the paper is organized as follows. In section 4.2, we motivate our analysis more fully by introducing the institutional context of emergency response systems, outlining the principal technological choices faced by these systems and local hospitals, and suggesting the main economic issues that arise in the analysis of these systems. Section 4.3 presents the data that we will use to conduct the analysis. Sections 4.4, 4.5, and 4.6 consider the determinants of adoption of emergency response systems, our analysis of productivity, and the role of the emergency response system in allocating patients to hospitals. Our concluding remarks suggest a number of directions for future research.

4.2 Emergency Response Systems: Background and Motivation

The goal of this section is to motivate our empirical analysis of emergency response systems through a description of the background and institutions of prehospital care. To do so, we review the operation of the emergency medical response system (in most communities, a 911 system), focusing in particular on potential productivity benefits. We further discuss the interaction between prehospital and in-hospital emergency care.

Finally, we describe the factors that lead to heterogeneity in the adoption of 911.

Emergency response systems are a public service providing a standardized and integrated method for local communities to respond to emergencies. Until the late 1960s, emergencies were reported to a telephone operator (whose training and equipment usually did not accommodate the efficient handling of emergency) or by directly contacting a particular public service agency (requiring individuals to find the seven-digit phone number for a particular agency and precluding integration among agencies). Under this ad hoc system, emergency response was often inappropriate to the particular situation—overreaction to minor crises coexisted with frequent underreactions to critical emergencies (Gibson 1977; Siler 1975). Following a model developed in Europe after World War II (most particularly the 9-9-9 system in Great Britain), the first 911 systems were introduced into the United States in 1968 (in Haleyville, Alabama, and Nome, Alaska). Shortly thereafter, federal legislation explicitly encouraged the development of 911 systems in local communities and ensured that the Bell System would reserve 911 for emergency service use (Pivetta 1995).

While the scope and particular details of many systems vary, 911 systems operate according to the following standard procedure:

An individual in an emergency dials 911.
Call is answered by a Public Service Answering Point (PSAP) operator.
A trained 911 call taker evaluates the caller's emergency and gathers necessary information (location, severity, etc.).
Call taker communicates with the appropriate emergency service agencies for dispatch to the emergency.

While 911 calls can be routed to many different geographical locations, the adoption of 911 usually entails some increase in the centralization of call taking, to avoid duplication of fixed costs and adoption costs of the relevant telecommunications equipment. Even if centralization remains unchanged, 911 almost inevitably increases the degree of coordination between call centers.

From the perspective of the productivity analysis for cardiac patients, the most important benefit of 911 systems is to reduce response time. Our focus on cardiac care allows us to assess a particular medical condition for which outcomes have been closely linked (at least in the clinical emergency services literature) to the effectiveness of the emergency response system and ambulance technology. According to a variety of medical sources (see, e.g., Cummins et al. 1991; Bonnin, Pepe, and Clark 1993; and Tresch, Thakur, and Hoffman 1989), several medical procedures can contribute to survival in the case of a cardiac incident, including CPR and defibrillation. In particular, the medical literature has tied patients' survival probability to reductions in the time elapsed between initial collapse of a patient and the administration of CPR and defibrillation (Lewis et al. 1982; Larsen et al. 1993). While CPR can be in principle conducted by a non-professional bystander (perhaps with over-the-phone instructions from a trained call taker), it is typically best performed by paramedics. Furthermore, defibrillation—electrical shock therapy to "reset" the electrical activity of the heart in the case of ventricular fibrillation (irregularity)—requires equipment that is transported in ambulances or available in hospitals. As a result, correct administration of CPR and/or defibrillation are dependent on the time it takes for an ambulance (equipped with a defibrillator) to arrive at the scene of an emergency.

As a mechanism for reducing response times, 911 systems have several advantages. First, they save time in the placement of the telephone call, since citizens are unlikely to have memorized the telephone number for the relevant agency. Further, the personnel who receive the first telephone call are trained to handle emergencies, as opposed to standard telephone operators or directory assistance personnel. Even when the appropriate agency is reached, decentralized call centers without 911 tend to assign telephone duties to personnel who also have other responsibilities. Specialization might be important for learning the details of a geographical area as well as for developing the skills required to gather information from emergency callers. However, there is potentially a cost to centralization in the cases where 911 is provided at a central location without Enhanced 911 capabilities, since workers may not be as familiar with addresses and geography when they are responsible for larger areas.

As 911 systems have evolved and diffused over the past 30 years, there have been several important advancements in the technology utilized to implement these systems. One main area for advancement has been the development of Enhanced 911 systems (E911), which utilize caller identification together with databases of addresses. To implement this automatic location identification feature, counties must first develop a system of addressing that provides unique street addresses to every residence (which often do not exist in rural areas) and develop a map of the county with all of these addresses. This system allows call takers to pinpoint the location of a caller almost instantaneously (the databases may include very precise information about the location of a telephone in a building or public place, and they can also include special information about individual health issues or disabilities).

There are a number of benefits to E911 technology. Of course, even when the caller knows the location and directions precisely, it takes time to communicate this information, and mistakes are easy to make with callers who are experiencing panic or fear. For the frequent cases where people do not know their exact address (they are visiting a friend or experience an emergency incident in a public place), the location information is even more valuable. Likewise, the location information can be crucial for callers who are children and for adults who do not speak English or are unable to speak. Furthermore, once address information can be communicated instantaneously, the call taker has more time to gather information about the severity of the emergency, and the call taker can further provide prearrival instructions to the caller. Finally, this system mitigates some of the costs of centralizing the call centers, since detailed geographic knowledge of an area is not essential.

After a call taker receives and establishes the location and severity of an emergency call, the dispatcher directs an ambulance to the scene of the emergency. The ambulance provides three related services: provision of immediate emergency care, transportation service to a hospital, and the exercise of (limited) discretion over the allocation of patients to particular local hospitals. Counties differ in their provision of ambulance services.[3]

A potential benefit of specialized personnel and coordinated 911 services is that scarce resources for ambulance services can be more efficiently allocated.[4] The dispatcher might have to choose whether to dispatch an ambulance equipped with advanced life support (ALS) facilities, or, alternatively, a less technically sophisticated basic life support (BLS) unit. This decision can be made more efficient when the call taker gathers the relevant information about the nature of the emergency. When such decisions are made in the absence of appropriate information, ambulances may not be available to answer higher priority calls, and average response times for high-priority cases will rise. In fact, a number of studies document the fact that many ambulance systems service a large number of superfluous calls, where ambulance service was not the best method for providing care (Gibson 1977; Smith 1988; Brown and Sindelar 1993). This literature tends to strongly support the increased use of sophisticated prioritization and computerization in the dispatching process. Coordinated and trained call takers and dispatchers can better utilize the scarce ambulance resources, and the adoption of computer-aided dispatching and other such solutions are more easily accomplished in systems that have E911.

In addition to the direct effect of the 911 system on the productivity of the emergency health care system, the emergency response system also affects the allocation of patients to hospitals. The ambulance personnel are instructed to use a standard protocol for allocating patients to hospi-

3. However, we have not collected detailed data about the ambulance services in different counties for this paper.

4. While we focus in the current paper on the choice of technology for a community's 911 system, there are also important differences among counties in terms of the human resource practices employed. In the context of medical emergencies, there has been a diffusion of "emergency medical dispatch" (EMD) systems that provide a more systematic way of handling particular emergencies. EMD systems enable call takers to provide medical instructions over the phone to bystanders (such as instructions for CPR) to reduce the time until key medical procedures are performed (such as CPR) and to maintain calm at an emergency site until ambulance care arrives.

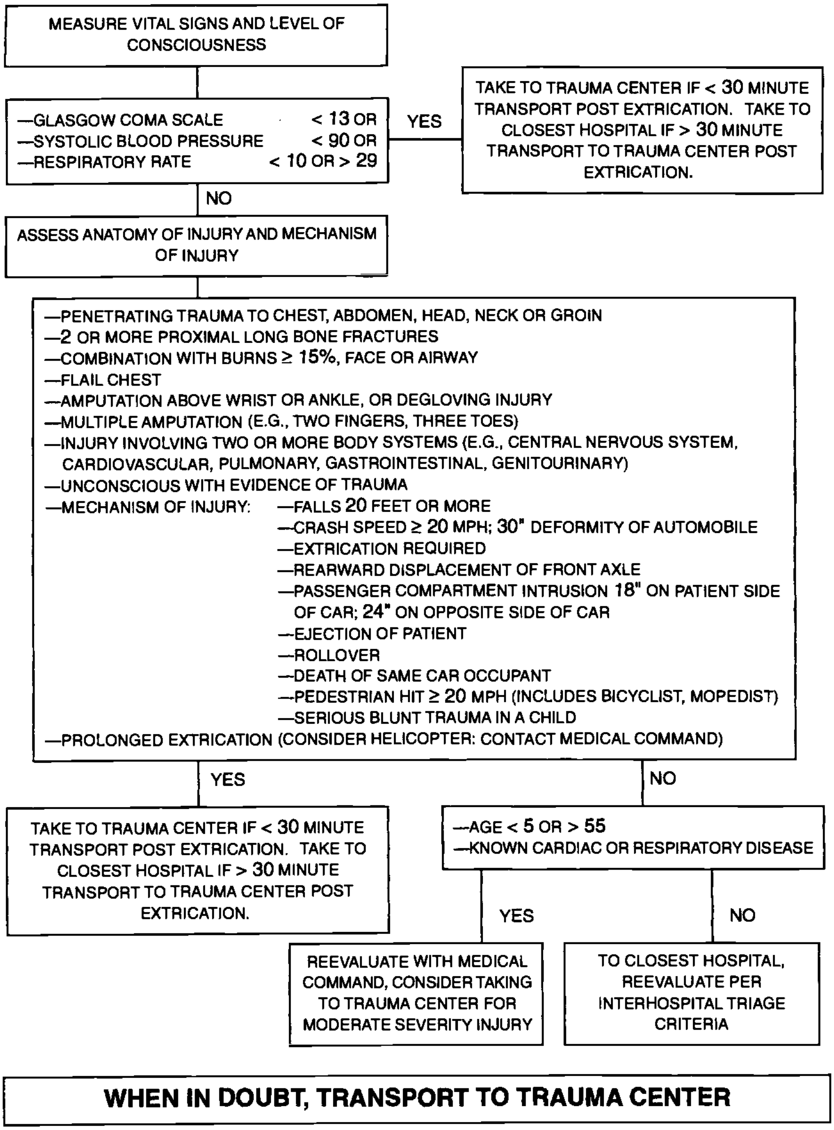

Fig. 4.1 County trauma protocol

tals (see fig. 4.1 for a representative county protocol). In figure 4.1, patients are allocated to hospitals according to a number of risk criteria, with more severe patients being allocated to the "trauma center" (which provides a certified level of emergency room services and technology) in most cases but to the geographically closest hospital if the nearest trauma center is greater than 30 minutes away from the site of the emergency. While the protocol provides "bright line" rules for most situations, ambulance personnel are given a limited amount of discretion about borderline cases and are also instructed to confirm some discretionary choices with "medical command." Thus, ambulance personnel, using agreed-upon protocols and their own judgment, resolve a trade-off between reduced transport time and allocating the patient to the hospital with the highest level of cardiac care facilities. By providing better dispatching, gathering more patient information prior to arrival, and shortening response time, higher levels of 911 service may allow the allocation of patients to hospitals to be more efficient. For example, when response time is shorter and dispatchers have more precise information about the patient's location, there will be more time to transport a cardiac patient to a hospital with specialized facilities.

The mechanism that allocates patients to hospitals can also have unintended consequences, in that it affects the incentives of hospitals to adopt various technologies. According to the triage protocols, certain patients should almost never be allocated to hospitals without a sufficient level of emergency services, and cardiac patients may tend to be allocated to hospitals known for cardiac care. Thus, hospitals may have a "business-stealing" incentive to increase the rating of their emergency room or their available technology (Vogt 1997). Anecdotal evidence suggests that hospitals are aware of the discretion of ambulance operators, although their response to this discretion is not always as sophisticated or expensive as increased technology adoption. In many localities, hospitals provide free supplies to the ambulances, as well as amenities for ambulance operators such as access to lounges supplied with food and beverages.

Empirically, there is wide variation across counties in the provision of 911 services. Some of the heterogeneity may be accounted for by efficiency considerations. For example, counties in which addresses are assigned systematically see lower benefits to E911. Differences in population may also account for differences in adoption across counties, since as a service with adoption costs and fixed costs, 911 should exhibit economies of scale, at least initially (systems that become too large may experience coordination costs). Further, the costs of adoption and implementation of 911 may vary across counties. Consider the nature of these costs. When adopting E911, it is necessary to assign new addresses, create new maps, and develop a computerized database, a process that is very labor-intensive and usually takes at least six months to a year to complete. Furthermore, the telephone equipment, caller identification database, and system of call-taker workstations must be procured and installed. While systematic data about the start-up costs of E911 is unavailable, based on several cases, we estimate that a typical county has a start-up cost of between $1 million and $4 million.

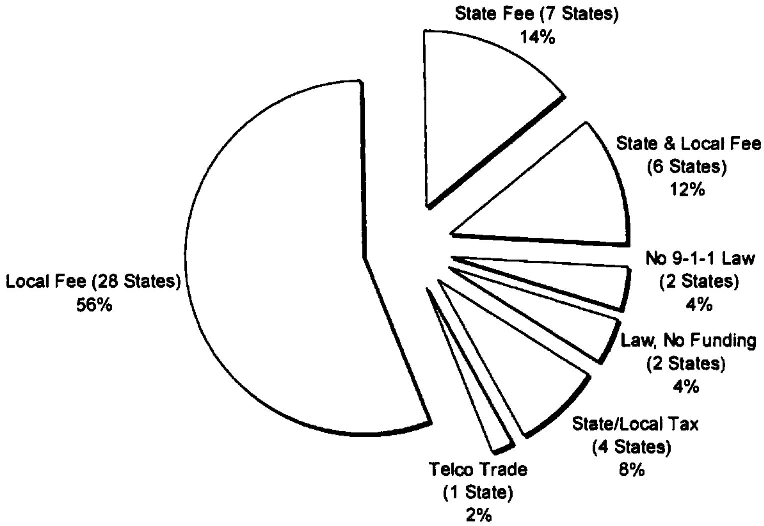

Fig. 4.2 911 Funding by state
Source: Adapted from Pivetta (1995, 135).

For example, consider Berks County, Pennsylvania, whose 1990 population was 336,000. Berks County reports that the capital start-up costs of its E911 system were approximately $3 million, while annual operating costs were over $2.3 million.[5] Its budget comes primarily from a tax on telephone lines ($0.97 per line each month) as authorized by state legislation. (Fig. 4.2 shows the national distribution of funding sources for 911 systems.) The Berks County 911 program employs nine call takers, two administrators, a programmer for its computer-aided dispatching software, and an administrative assistant.

In addition to capital costs, there are other factors that affect the adoption of 911 systems; we explored these motivations in informal interviews of administrators and regulators in several states. We found that in smaller counties, early adoption of E911 was often the result of the actions of a highly self-motivated and informed government employee. Because many different public and private agencies are involved in the implementation process (the post office, utility companies, and telephone companies), political factors and bureaucratic barriers may slow adoption. While in large counties there may be personnel assigned exclusively to this task, smaller counties tend to assign the same personnel to many different tasks, and the incentives as well as information required to organize an effort for

5. This number does not include overhead incurred by the Berks County Communication Center, which handles many calls in addition to 911 calls. For further information, see http://www.readingpa.com/911/.

adoption may be lacking. The adoption of a centralized 911 system may lead small, local police departments, as well as private ambulance dispatching services, to lose employment as well as local autonomy; these agencies may be able to block adoption. Finally, as a publicly provided service, public demand for the system will also play a role, where this demand depends not only on factors such as income but also on the political views of the citizens about government services.

4.3 The Data

As mentioned earlier, little previous empirical research has been done on the prehospital emergency system. Thus, in this paper we choose to conduct our analysis at several different levels of aggregation: individual, hospital, and county. Each of these sources of data allow us to address different questions about the adoption and productivity of elements of the emergency system. Tables 4.1, 4.2, and 4.3 provide definitions, sources, and means and standard deviations for all variables.

4.3.1 County-Level Variables

For the purposes of this paper, we characterize the prehospital emergency infrastructure and its determinants at the county level. Unfortunately, we are not aware of a comprehensive accounting of 911 practices in the United States. Within Pennsylvania, we gathered information about 911 provision through publicly available sources and telephone interviews. At the national level, we made use of a survey administered in 1995 by the National Emergency Number Association (NENA), a national advocacy organization for 911 systems. As a result, our national sample of counties is limited to 772 counties who completed the NENA survey and who provided answers that allowed us to characterize the 911 system at the county level.[6]

For each county, we organize our analysis around a three-tier characterization of the 911 system: whether there is a 911 system at all (NO 911) and whether it is a basic 911 (BASIC 911) or enhanced (ENHANCED 911) system. In the national sample, 75 percent of these counties have adopted the highest level of service (ENHANCED 911), illustrating that E911 has been diffused substantially (911_LEVEL is simply a variable that is 0, 1, or 2, depending on whether the system is NO 911, BASIC 911, or ENHANCED 911). However, the selection of counties who responded to NENA's survey is biased toward systems with higher levels of 911 service,

6. A large number of responses in fact reflected the technology and training choices of smaller 911 systems (e.g., townships or even university campuses). We selected out only those observations who reported that they were the PRIMARY PSAP center and who stated that their coverage was countywide. This selection process underrepresents counties for which there is no countywide 911 system.

Table 4.1 **Variables and Definitions**

	Definition	Source
Outcome measures		
DEAD	Dummy variable = 1 if spell outcome = dead	PA EMS
TIME_TO_SCENE	Time (mins) from dispatch to arrival at scene	PA EMS
TIME_AT_SCENE	Time (mins) of EMS unit at scene	PA EMS
TIME_TO_HOSP	Time (mins) from scene to hospital	PA EMS
911 level		
NO 911	No countywide 911 emergency response	NENA; telephone survey
BASIC 911	Countywide 911; no automatic location identification (ALI)	NENA; telephone survey
ENHANCED 911	Countywide 911 with ALI	NENA; telephone survey
911_LEVEL	No 911 = 0; Basic 911 = 1; Enhanced 911 = 2	NENA; telephone survey
Patient characteristics		
MALE	Dummy = 1 if sex = male	PA EMS
AGE	Patient age (years)	PA EMS
CARDIAC ARREST	Dummy = 1 if EMS unit records cardiac arrest incident	PA EMS
DEFIBRILLATE	Dummy = 1 if patient receives defibrillation prior to arrival at hospital	PA EMS
GLASGOW ##	Glasgow trauma score dummies (15 = Least Severe; 3 = Most Severe)	PA EMS
GLASGOW 0	Glasgow score = 0 (Unknown or Unrecorded)	PA EMS
Insurance status		
MEDICARE	Dummy = 1 if insurance status = Medicare	PA EMS
MEDICAID	Dummy = 1 if insurance status = Medicaid	PA EMS
PRIVATE	Dummy = 1 if insurance status = private or government	PA EMS
SELF PAY	Dummy = 1 if insurance status = self-pay	PA EMS
OTHER	Dummy = 1 if insurance status = other	PA EMS
Hospital characteristics		
URGENT CARE CENTER	Dummy = 1 if certified urgent care center	AHA
CATH LAB	Dummy = 1 if cardiac catheterization lab present	AHA
OPENHEART FAC	Dummy = 1 if open heart surgery facility	AHA
TRAUMA CNTR LEVEL	Dummy = 1 if clinic = 2 if emergency room = 3 if trauma facilities present = 4 if certified county trauma hospital	AHA

(*continued*)

Table 4.1 (continued)

	Definition	Source
EMERGENCY ROOM VOLUME	Total no. of emergency room visits in 1995 (in thousands)	AHA
HOSPITAL DOCTORS	No. of full-time doctors on staff in hospital	AHA
HOSPITAL RESIDENTS	No. of medical residents on staff in hospital	AHA
County hospital infrastructure		
CERTIFIED TRAUM CNTR	Dummy = 1 if county contains at least one hospital with TRAUMA CNTR LEVEL = 4	AHA
HOSP PER SQ. MILE	No. of hospitals in county/No. of square miles	AHA/CCDB
COUNTY CARDIAC PATIENTS	No. of recorded cardiac incidents in 1995	PA EMS
County demographics (reference year = 1992)		
POPULATION	County population/1,000	CCDB
DENSITY	Population/county square miles	CCDB
INCOME PER CAP	County-level income per capita/1,000	CCDB
CRIMERATE	Crime rate (incidents per 100,000 pop.)	CCDB
VCRIMERATE	Violent crime rate (incidents per 100,000 pop.)	CCDB
POLICE EXP	1992 level of police expenditures	COG
HEALTH EXP	1992 level of public health expenditures	COG
% REPUBLICAN	1992 Republican voter percentage (presidential)	CCDB
% PEROT	1992 Perot voter percentage (presidential)	CCDB
State legislation		
911_TRAIN_LAW	Legislation implemented for 911 Telecommunicator training requirements	NENA
911_TRAIN_PLAN	Legislation approved but not implemented for 911 Telecommunicator training requirements	NENA

Note: The natural logarithm of a variable will be denoted L VARIABLE NAME.

especially undercounting counties with no countywide 911 system; in Pennsylvania, where we have a comprehensive accounting of the counties, 30 of the 54 counties had E911 at the start of 1995 (see fig. 4.3).

In addition to the county-level variables, we include in our analysis two "911" variables drawn from NENA state-level surveys that indicate whether there is implemented legislation guiding the administration of 911 systems (in particular, governing training policies for workers using the systems) (911_TRAIN_LAW) or whether legislation has been passed but not yet implemented (911_TRAIN_PLAN). These variables are intended

Table 4.2 **Summary Statistics (county-level averages)**

	Pennsylvania Sample		National Sample	
	Mean	Standard Deviation	Mean	Standard Deviation
NO. OF COUNTY/SYSTEMS	58.000[a]		722.0000	
911 level				
NO 911	0.1897	0.3955	0.0692	0.2541
BASIC 911	0.2759	0.4509	0.1731	0.3786
ENHANCED 911	0.5345	0.5032	0.7576	0.4288
County hospital infrastructure				
CERTIFIED COUNTY TRAUMA CENTER	0.2586	0.4417	0.1898	0.3923
HOSP PER SQ. MILE	0.0072	0.0215		
COUNTY CARDIAC PATIENTS	1,264.8800	898.2086		
Demographics				
POPULATION	201.5020	280.0837	192.5940	370.3810
DENSITY	0.5084	1.5455	0.3331	0.7796
INCOME PER CAP	12.3244	2.6010	12.5994	2.9939
VCRIMERATE (CRIME RATE FOR NATIONAL SAMPLE)	0.0023	0.0021	0.0410	0.0234
POLICE EXP	16.1920	49.0941	15.4987	44.0724
HEALTH EXP	13.7416	40.4254	5.9974	14.4659
% REPUBLICAN	39.0000	7.6273	38.8680	7.8322
% PEROT	22.1622	3.3542	21.6440	6.1476
LAWSTRD	1.0000	0.0000	0.4626	0.4989
LAWPLAN	0.0000	0.0000	0.3518	0.4778

[a]Out of 54 Pennsylvania counties for which we observe the 911 level, 4 experienced midyear changes, yielding 58 "county system" observations.

to be proxies for the level of administrative information and assistance provided by the state.

We further gathered a variety of demographic, political, and economic data at the county level. In addition to a number of familiar demographic characteristics (POPULATION, DENSITY, INCOME PER CAPITA, CRIMERATE, POLICE EXP, HEALTH EXP, each drawn from the *City and County DataBook* or the *Census of Governments*), we also characterize the political climate of a community by the presidential voting shares from the 1992 election. This election is especially interesting because of the strong showing of Perot, allowing a somewhat more nuanced measure of a county's political demand for public expenditures (Perot voters were noted for their strong beliefs in limited government).

4.3.2 Hospital-Level Variables

Our information about hospitals is obtained from the American Hospital Association (AHA) annual hospital inventory survey. We use this infor-

Table 4.3 **Patient-Level Summary Statistics (Pennsylvania sample only)**

	Mean	Standard Deviation
NO. OF COUNTIES	54.0000	
NO. OF PATIENT OBS	24,664.0000	
Outcome measures		
DEAD	0.0711	0.2571
TIME_TO_SCENE	9.1251	6.0180
TIME_AT_SCENE	15.9059	7.6573
TIME_TO_HOSP	13.2354	9.6674
911 level		
NO 911	0.0827	0.2754
BASIC 911	0.1397	0.3467
ENHANCED 911	0.7777	0.4158
Patient characteristics		
MALE	0.4799	0.4996
AGE	69.8678	14.1957
CARDIAC ARREST	0.1043	0.3057
DEFIBRILLATE	0.3999	0.4899
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown)		
GLASGOW SCORE (EXCLUDING GLASGOW = 0)	14.2011	2.7239
GLASGOW 0	0.0442	0.2056
Insurance status		
MEDICARE	0.6627	0.4728
MEDICAID	0.0516	0.2212
PRIVATE	0.1885	0.3911
SELF PAY	0.0115	0.1067
OTHER	0.0358	0.1859
Hospital characteristics (based on patient allocation)		
URGENT CARE CENTER	0.2172	0.4123
CATH LAB	0.6703	0.4701
OPENHEART FAC	0.2940	0.4556
TRAUMA CNTR LEVEL	3.1670	0.4486
HOSPITAL DOCTORS	13.7234	19.3413
HOSPITAL RESIDENTS	27.2592	72.0307
EMERGENCY ROOM VOLUME	29.9091	12.7018

mation to provide information at three different levels of analysis. First, when we study the incentives of hospitals to adopt technology, we consider the availability of hospital technology at *any* hospital within a county. For example, CERTIFIED TRAUM CNTR represents the presence of a certified trauma center in a given county, while HOSP PER SQ. MILE represents the density of hospitals. We also consider the number of recorded cardiac incidents that required ambulance service in 1995 (COUNTY CARDIAC PATIENTS). Second, in our patient-level productivity analysis, we link hospital characteristics to our patient-level data-

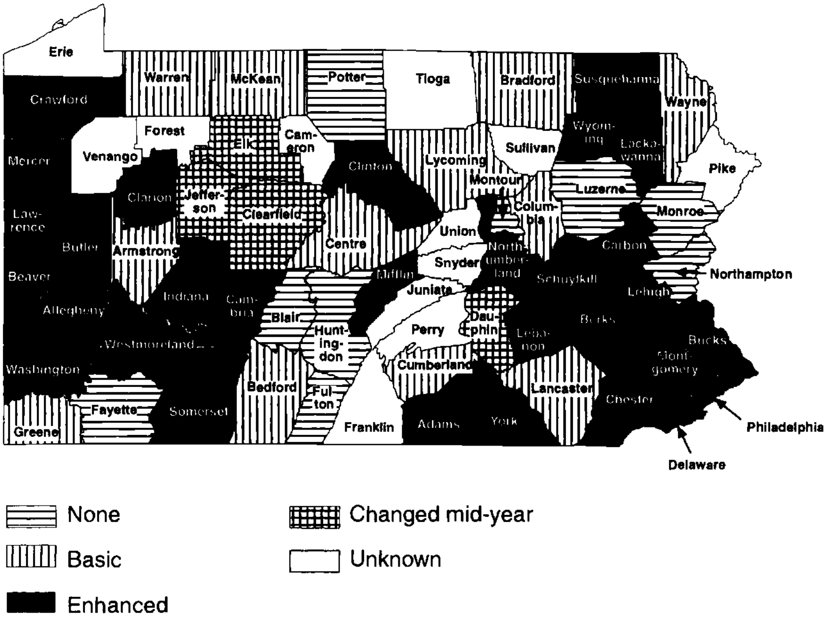

Fig. 4.3 Distribution of emergency response systems, by county

base in order to control for hospital quality as well as to analyze the allocation process that assigns patients to hospitals. Third, we consider the hospital as the unit of analysis when we consider how technology investments interact with the share of cardiac patients who are treated in a given hospital.

For each hospital, we consider three main types of variables. First, we characterize the generic emergency infrastructure for a given hospital by identifying whether the hospital is an urgent care provider (URGENT) and by identifying the level of certified emergency care (TRAUMA CNTR LEVEL). In our analysis of individual data, we examine the case of cardiac care and we also look specifically at the cardiac care facilities provided by each hospital. In particular, we observe whether a hospital has a cardiac catheterization lab (CATHETER) and whether it has open heart surgery capability (OPENHEART). Finally, we characterize the overall features of each hospital, including its size (EMERGENCY ROOM VOLUME; HOSPITAL DOCTORS) and the number of residents (HOSPITAL RESIDENTS).

4.3.3 Patient-Level Variables

Our patient-level variables are drawn from a database of every ambulance ride in Pennsylvania that could be linked to a hospital discharge during 1995 (approximately 170,000 observations). This data set is gathered by the Pennsylvania Department of Health and has only recently been made available to a limited number of researchers; we are not aware of prior work on this database (or on a similar ambulance-level database) by health care economists.

The information provided in this patient-level data is unusually rich. First, there are several indicators associated with the responsiveness of the 911 system. We analyze three different measures of the timeliness of ambulance response: the amount of time it takes to get to the scene of an emergency (TIME_TO_SCENE), the amount of time spent at the scene (TIME_AT_SCENE), and the amount of time elapsed from when the ambulance leaves the scene to the time when the ambulance arrives at the hospital (TIME_TO_HOSP).

In the next sections, we will examine how the response time measures vary with other features of the medical care system. To better motivate that type of analysis, we restrict our analysis of the Pennsylvania data to the case of cardiac incidents. One of the main advantages of analyzing the case of cardiac incidents is that, in contrast to many data sets, there are in fact a number of quite precise indicators of the level of severity of each patient. In particular, each patient is assigned a Glasgow score, which is a number between 0 and 15 that indicates the severity of the heart attack (lower numbers imply higher severity, with 3 being the worst and 0 indicating "unknown" or "missing"). While the bulk of observations are coded with the weakest severity (GLASGOW = 15), there exists a substantial minority for which there is variation in the data. We are also able to observe whether the incident is believed to be a cardiac arrest or simply a cardiac incident (CARD_ARR = 1 or 0).

In addition to these measures of severity, the data includes relatively detailed information about each individual in the data set, including insurance status, age, and sex. We also observe some information about the types of procedures administered by the emergency response paramedics, including whether the patient received defibrillation treatment prior to arrival at the hospital. However, since the decision to defibrillate a patient is conditioned on patient characteristics that are unobserved to the econometrician, this variable serves mainly as a control in our analysis.

Finally, we are able to observe some concrete measures associated with patient outcomes. In our main analysis, we will focus on the most extreme of these measures, DEAD: whether or not the patient dies from the incident, either in the emergency room or in the hospital afterward.

4.4 The Determinants of the 911 System Adoption

Table 4.4 summarizes the characteristics of three groups of counties in Pennsylvania: those with no 911, Basic 911, and Enhanced 911. Because

Table 4.4 **County Characteristics by 911 Level (means of county-level averages)**

	County 911 Level			
	No 911	Basic 911	Enhanced 911	Enhanced 911 (Excluding 4 Largest Counties)
NO. OF COUNTIES	11.0000	16.0000	31.0000	27.0000
NO. OF CARDIAC OBS	2,039.0000	3,445.0000	19,180.0000	10,993.0000
Outcome measures				
DEAD	0.0567	0.0565	0.0680	0.0671
TIME_TO_SCENE	11.7469	11.2579	9.8656	10.1360
TIME_AT_SCENE	12.8364	14.3900	15.7645	15.5155
TIME_TO_HOSP	16.6352	15.2248	13.7586	14.2163
County hospital infrastructure				
CERTIFIED TRAUM CNTR	0.0000	0.1875	0.3871	0.2963
HOSP PER SQ. MILE	0.0032	0.0024	0.0111	0.0040
COUNTY CARDIAC PATIENTS	255.2500	267.3300	671.3667	421.8077
Demographics				
POPULATION	109.0007	106.6353	283.2884	172.4249
DENSITY	0.1756	0.1405	0.8164	0.2807
INCOME PER CAP	11.2406	11.6869	13.0380	12.5100
CRIMERATE	0.0018	0.0018	0.0026	0.0020
POLICE EXP	4.2037	4.3714	26.5468	7.9701
HEALTH EXP	2.3600	3.5011	23.0656	8.4577
% REPUBLICAN	39.9091	41.6875	37.2903	38.0741
% PEROT	23.6667	22.5455	21.7826	22.5500

four counties are significantly larger, more dense, and have more hospitals than the others, we also report the counties with E911 excluding the four largest counties (we will also report specifications that exclude these four counties in our subsequent regression analysis). There are some systematic differences between the demographic characteristics of the counties that have made different adoption decisions about 911. The largest and most densely populated counties, as well as those with the highest income and largest police and health budgets, tend to have adopted Enhanced 911.

When comparing the counties with no 911 to the counties with Basic 911, it is interesting to note that they are remarkably similar in terms of density, crime, income, and hospitals per mile. Figure 4.3 illustrates that many contiguous counties with similar geographic features have different levels of 911. The main differences are that the counties with Basic 911 have higher populations, higher expenditures, and more Perot voters. Since 911 systems involve fixed costs, the differences in adoption appear to be consistent with efficiency motivations on the part of the counties. However, since the county boundaries are purely political distinctions, this finding raises the question of whether between-county cooperation in the provision of 911 services might allow more citizens to be served by 911. The state of Vermont recently implemented a statewide 911 system, perhaps recognizing the economies of scale associated the provision of the service at the state level.

As described in section 4.2, we expect that the level of 911 technology will respond to political demand as well as demographic factors related to the efficiency of the service in a particular locality. While much of our productivity analysis will focus on a subset of cardiac patients in Pennsylvania, a within-state analysis can provide only limited insight as to the factors that determine the allocation of 911 services (and their productivity benefits) to different subsets of the population. Thus, in table 4.5, we consider the determinants of adoption of the level of 911 service in a national cross-section of counties. As expected, POPULATION is significantly correlated with adoption; politically, counties with a relatively high proportion of Perot voters tend to adopt lower levels of 911, consistent with the emphasis of the Perot movement on limited government expenditure. Also, counties in states with regulations about training had higher levels of 911 adoption. This legislation either requires or recommends standardized training programs in association with 911 programs, and may further proxy for the institutional support for 911 provided by the state boards that oversee 911 centers. We interpret this result to indicate that states that provide legislative support and guidance for 911 systems have a higher propensity to adopt 911 services. Thus, we conclude that 911 adoption responds to efficiency motivations as well as to political and regulatory factors that may be unrelated to efficiency.

The latter two specifications in table 4.5 include a variable that measures the highest level of in-hospital emergency care offered in the county (in addition to the controls described above). Even though the unconditional correlation between 911 and the level of in-hospital emergency care is positive (.19) and significantly different from zero, most of that positive relationship is accounted for by common factors that affect the adoption of both (e.g., population). Thus, despite the potential for strategic complementarities between hospital technology adoption and 911 services when higher levels of 911 better allocate patients to high-technology hospitals, we do not see strong evidence of this interaction in our national sample.

4.5 The Impact of 911 Systems and Hospital Choice on Ambulance Response Times and Mortality: The Case of Cardiac Arrest

We now turn to an analysis of individual cardiac incidents. We evaluate the effects of the 911 infrastructure on patient outcomes, as well as on several "intermediate inputs" to patient outcomes, in particular, several components of response time. We focus on intermediate inputs for several

Table 4.5 911 Demand Regressions (national sample)

	Dependent Variable = 911 Level			
	Base Regression (OLS)	Base Regression (Ordered Logit)	Include County Hospital Infrastructure	Include Hospital Infrastructure (Ordered Logit)
County hospital infrastructure				
CERT. TRAUMA CNTR.			−0.06458	−0.44596
			(0.06221)	(0.29835)
County demographic characteristics				
L POPULATION	0.11172	0.37180	0.11555	0.37754
	(0.02972)	(0.13783)	(0.02995)	(0.13877)
DENSITY	0.000004	0.00078	0.000008	0.00088
	(0.000037)	(0.00069)	(0.000037)	(0.00070)
INCOME PER CAP	0.01207	0.06675	0.01266	0.06894
	(0.00956)	(0.05483)	(0.00958)	(0.05516)
CRIMERATE	0.27501	4.34417	0.33910	4.77066
	(1.14780)	(5.69929)	(1.14940)	(5.74605)
POLICE EXP	−0.00108	−0.01212	−0.00104	−0.01176
	(0.00081)	(0.00747)	(0.00081)	(0.00781)
HEALTH EXP	0.00088	0.04322	0.00113	0.04601
	(0.00243)	(0.03065)	(0.00244)	(0.03077)
County political characteristics				
% REPUBLICAN	−0.00332	−0.01023	−0.00344	−0.01050
	(0.00284)	(0.01282)	(0.00285)	(0.01286)
% PEROT	−0.00854	−0.04217	−0.00873	−0.04301
	(0.00402)	(0.01774)	(0.00386)	(0.01781)
State legislation				
911_TRAIN_LAW	0.16148	0.47014	0.15724	0.46095
	(0.05926)	(0.23082)	(0.05940)	(0.23085)
911_TRAIN_PLAN	0.26570	1.04053	0.26365	1.04598
	(0.06372)	(0.27448)	(0.06375)	(0.27465)
Constant	0.41650		0.38349	
	(0.31374)		(0.31533)	
Ord. logit parameters		Insignificant		Insignificant
Observations	722	722	722	722
Log-likelihood		−444.51963		−443.44308
R-squared	0.1192		0.1206	

reasons. First, since 911 provides service benefits through an investment in information technology, we are inherently interested in disentangling the extent to which 911 provides services that are more timely and better respond to patient characteristics. Second, mortality is a very noisy measure of the productivity of the emergency response system, and even in our large data set, we see only a few thousand deaths from cardiac incidents, and only a few hundred in the counties without E911 systems.

Third, even in these cases, we expect that the policy variables will have a significant impact on outcomes in only a small subset of the cases. Many of the patients who die would die regardless of the response time; and many patients who survive did not rely heavily on the emergency response system. However, if we establish that 911 reduces response time, we can rely on a number of clinical studies that provide direct evidence about the benefits of faster response times for mortality.

Building on our analysis from section 4.2, we predict that the first component of response time, TIME_TO_SCENE, should be lower when counties are able to gather address and location information more rapidly and precisely, and when ambulance resources are allocated efficiently (recall cardiac emergencies are high-priority events). The second component, called TIME_AT_SCENE, should be longer when more treatment is given prior to moving a patient; it should also be longer when patients are located in high-rise buildings or large complexes. The final component, TIME_TO_HOSP, should be lower when dispatchers are able to provide better assistance to ambulance drivers in terms of routing and directions to hospitals from varied locations. On the other hand, TIME_TO_HOSP should reflect a trade-off between the benefits of arriving at a high-quality hospital and the benefits of receiving hospital attention as soon as possible. The impact of 911 on this trade-off might be to encourage ambulances to take somewhat longer rides, if time has been saved in other parts of the process.

Of course, both TIME_TO_SCENE and TIME_TO_HOSP will depend on the location of a given patient relative to the hospitals, and variation across counties in the average proximity of patients to hospitals is a potential source of unobserved heterogeneity that must be considered in interpreting our results. We partially alleviate this problem in several of our specifications by including controls for TIME_TO_HOSP in the regressions concerning TIME_TO_SCENE, and vice versa. For example, in the analysis of the determinants of TIME_TO_SCENE, the variable TIME_TO_HOSP acts as a control for the remoteness of the patient's location.

Table 4.6 reports the means of patient-level variables according to the level of 911 provided in a given county. Only 2,039 of the 24,664 cardiac incidents occurred in counties without 911. The mortality rates are very similar in counties with no 911 or Basic 911: Approximately 6.5 percent of cardiac emergencies result in death. In contrast, even excluding the largest four counties, the average mortality rate in counties with E911 is 7 percent (see fig. 4.4 for the distribution of county mortality rates). We further see that counties with higher levels of 911 have lower average TIME_TO_SCENE and TIME_TO_HOSP, while they have longer TIME_AT_SCENE. We will explore all of these relationships in more detail in our regression analysis.

The patient characteristics, trauma scores, and insurance status variables

Table 4.6 **Distribution of Pennsylvania 911 Level (patient-level averages)**

	County 911 Level			
	No 911	Basic 911	Enhanced 911	Enhanced 911 (Excluding 4 Largest Counties)
NO. OF COUNTIES	11.0000	16.0000	31.0000	27.0000
NO. OF CARDIAC OBS	2,039.0000	3,445.0000	19,180.0000	10,993.0000
Outcome measures				
DEAD	0.0652	0.0668	0.0726	0.0707
TIME_TO_SCENE	10.8759	10.1756	8.7503	9.2553
TIME_AT_SCENE	13.9897	14.2517	16.4068	15.4553
TIME_TO_HOSP	15.8141	15.5509	12.5453	13.8118
Patient characteristics				
MALE	0.4723	0.5013	0.4757	0.4825
AGE	70.0844	70.0673	69.8090	70.0183
CARDIAC ARREST	0.0510	0.0456	0.1205	0.0494
DEFIBRILLATE	0.5311	0.3358	0.3974	0.3879
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown)				
GLASGOW 0	0.0711	0.0761	0.0357	0.0259
GLASGOW 3	0.0436	0.0369	0.0455	0.0432
GLASGOW 4–9	0.0118	0.0134	0.0153	0.0121
GLASGOW 10–12	0.0098	0.0171	0.0171	0.0140
GLASGOW 13–14	0.0392	0.0360	0.0414	0.0388
GLASGOW 15	0.8244	0.8206	0.8450	0.8659
Insurance status				
MEDICARE	0.6714	0.6572	0.6628	0.6738
MEDICAID	0.0520	0.0453	0.0527	0.0505
PRIVATE	0.1751	0.1878	0.1900	0.1846
SELF PAY	0.0181	0.0125	0.0106	0.0142
OTHER	0.0451	0.0229	0.0372	0.0287
County hospital infrastructure				
CERTIFIED TRAUM CNTR	0.0000	0.0967	0.6380	0.3684
HOSP PER SQ. MILE	0.0040	0.0033	0.0284	0.0050
COUNTY CARDIAC PATIENTS	331.7543	687.1756	1,467.8430	778.5308
Demographics				
POPULATION	169.3076	226.2671	603.5968	261.0682
DENSITY	0.2812	0.2851	2.1253	0.3925
INCOME PER CAP	11.8924	13.3673	14.8970	14.0029
CRIMERATE	0.0020	0.0020	0.0045	0.0025
POLICE EXP	7.1510	10.4612	74.1042	13.4522
HEALTH EXP	3.9969	8.7517	61.2895	13.6651
% REPUBLICAN	36.9716	47.8389	35.3231	38.1708
% PEROT	21.9413	19.9428	19.9104	22.4042
Hospital characteristics				
URGENT CARE CENTER	0.0329	0.3759	0.2082	0.1957
CATH LAB	0.2398	0.6453	0.7205	0.6499
OPENHEART FAC	0.1525	0.3840	0.2929	0.2996
TRAUMA CNTR LEVEL	3.0000	3.0581	3.2049	3.2105
HOSPITAL DOCTORS	4.1187	9.6569	15.4748	14.7493
HOSPITAL RESIDENTS	5.3198	12.0136	32.3299	17.4391
EMERGENCY ROOM VOLUME	30.4250	27.0173	30.3736	31.0908

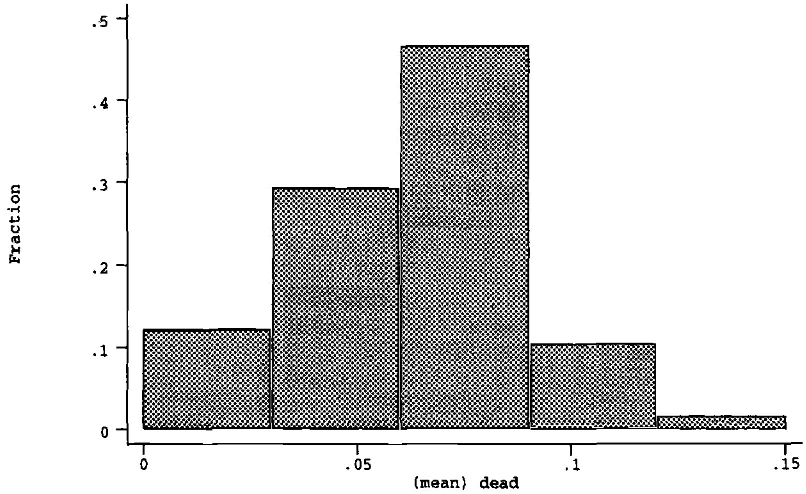

Fig. 4.4 County-level mortality distribution

have almost identical means across the no 911, Basic 911, and Enhanced 911 categories, with a few exceptions. First, the Glasgow score variables have different means in Enhanced 911 counties. Further, a much larger percentage of patients reported cardiac arrest in the Enhanced 911 group. Finally, many more patients reported defibrillation (before reaching the hospital) in the no 911 counties. This might be due to differences in scoring or poor recordkeeping in a few counties; it could also reflect real differences in the composition and treatment of emergencies, or differences in the availability of defibrillators in ambulances.

It is also worth noting the large differences between patients in no 911 counties and other counties in the level of technology possessed by the hospital that receives the patients. None of the no 911 patients received treatment in a certified trauma center, and only a quarter went to hospitals with cardiac catheterization laboratories. Likewise, the emergency room volume and size of hospitals is much lower in no 911 counties. There are also significant differences between Basic and Enhanced 911 counties in the provision of hospital care, but these differences are not as dramatic once the four largest counties are excluded.

Now consider the effects of 911 technology on the various components of response time, beginning with the time elapsed between the dispatch of a 911 call and the arrival at the emergency (TIME_TO_SCENE) (table 4.7). There are four specifications, which include a number of patient-level as well as county-level covariates (the results in tables 4.7–4.9 about the effects of patient-level characteristics are generally robust to specifications that include county fixed effects instead of county-level covariates). The

Table 4.7 **Time-to-Scene Equation**

	Dependent Variable = L TIME_TO_SCENE			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
Time controls				
L TIME_AT_SCENE		−0.13163	−0.15461	−0.19951
		(0.00654)	(0.00763)	(0.02159)
L TIME_TO_HOSP		0.32575	0.3462	0.36371
		(0.00507)	(0.00607)	(0.02057)
911 level				
NO 911	0.09383	0.01831	0.05215	0.08953
	(0.01698)	(0.01557)	(0.01656)	(0.07063)
BASIC 911	0.07538	0.0222	0.00226	0.13546
	(0.01341)	(0.01228)	(0.01261)	(0.04305)
Patient characteristics				
MALE	0.03631	0.01558	0.01846	0.04848
	(0.0083)	(0.00759)	(0.00924)	(0.02857)
AGE	0.00745	0.00398	0.00197	0.01683
	(0.00205)	(0.00188)	(0.00252)	(0.0076)
AGE_SQUARED	−0.00006	−0.00002	−0.00001	−0.00011
	(0.00002)	(0.00001)	(0.00002)	(0.00006)
CARDIAC ARREST	−0.12503	−0.06098	0.05545	0.15153
	(0.01787)	(0.01635)	(0.03558)	(0.11695)
DEFIBRILLATE	0.03474	0.02764	0.02735	0.02532
	(0.00846)	(0.00773)	(0.0095)	(0.03216)
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown)				
GLASGOW 0	1.60486	1.33791	0.41029	−0.05927
	(0.20163)	(0.18496)	(0.22467)	(0.18582)
GLASGOW 3	1.63347	1.41933	0.41626	−0.10982
	(0.20315)	(0.18649)	(0.22637)	(0.18081)
GLASGOW 4–9	1.6558	1.4468	0.47398	
	(0.20322)	(0.18644)	(0.22688)	
GLASGOW 10–12	1.70663	1.43213	0.49918	−0.17747
	(0.20283)	(0.18607)	(0.22608)	(0.18852)
GLASGOW 13–14	1.6681	1.39132	0.45937	0.0092
	(0.20118)	(0.18456)	(0.22433)	(0.15863)
GLASGOW 15	1.6887	1.38023	0.47959	−0.08971
	(0.20057)	(0.18403)	(0.22347)	(0.1426)
Insurance status (excluded category = Medicare)				
MEDICAID	−0.08647	−0.0497	−0.02478	0.1198
	(0.02068)	(0.0189)	(0.02335)	(0.06903)
PRIVATE	−0.00113	−0.01811	−0.02074	−0.02352
	(0.01306)	(0.01193)	(0.01476)	(0.04388)
SELF-PAY	−0.00863	−0.0371	−0.0866	−0.27909
	(0.03815)	(0.03484)	(0.03826)	(0.20312)

(*continued*)

Table 4.7 (continued)

	Dependent Variable = L TIME_TO_SCENE			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
OTHER	−0.01691	−0.0206	−0.01409	0.10725
	(0.02288)	(0.0209)	(0.02733)	(0.06999)
County hospital infrastructure				
CERT. TRAUM CNTR	0.15789	0.09753	0.13947	
	(0.01474)	(0.01349)	(0.0196)	
L HOSP PER SQ. MILE	−0.12588	−0.04815	−0.00084	
	(0.01189)	(0.01092)	(0.01412)	
L COUNTY CARDIAC PATIENTS	−0.0567	−0.08468	−0.10222	
	(0.01177)	(0.01077)	(0.01176)	
County demographics				
L POPULATION	−0.09277	−0.03693	0.0374	
	(0.03064)	(0.02812)	(0.02924)	
DENSITY	0.0315	0.02544	−0.33748	
	(0.0055)	(0.00505)	(0.04916)	
L INCOME PER CAP	0.10874	0.22698	0.72577	
	(0.03698)	(0.03388)	(0.04689)	
VCRIMERATE	6.98859	9.77737	−6.69225	
	(4.24895)	(3.88727)	(4.69215)	
L POLICE EXP	0.06323	0.03356	−0.03753	
	(0.0224)	(0.02049)	(0.0219)	
L HEALTH EXP	−0.013	−0.02067	−0.01945	
	(0.00422)	(0.00386)	(0.00403)	
Hospital characteristics				
URGENT CARE CENTER	−0.03722	−0.04101	−0.03001	
	(0.01138)	(0.0104)	(0.01389)	
CATH LAB	−0.03328	−0.04442	−0.04749	0.20105
	(0.01185)	(0.01084)	(0.01375)	(0.04967)
OPENHEART FAC	0.02769	0.0203	0.02798	
	(0.01243)	(0.01137)	(0.01865)	
TRAUMA CNTR LEVEL	−0.06379	−0.04453	−0.04719	
	(0.01181)	(0.01079)	(0.01872)	
EMERGENCY ROOM VOLUME	−0.00031	0.00046	−0.00073	0.00614
	(0.00025)	(0.00039)	(0.00054)	(0.05292)
HOSPITAL DOCTORS	0.00023	−0.00075	−0.00039	−0.01573
	(0.00007)	(0.00023)	(0.00052)	(0.04498)
HOSPITAL RESIDENTS	0.00043	0.00003	0.00102	
	(0.00043)	(0.00007)	(0.00036)	
Constant				1.241
				(0.31835)
Observations	24,664.0000	24,664.0000	16,477.0000	1,635.0000
R-squared	0.7040	0.7170	0.7170	0.2774

base regression includes 911 dummies, patient-level variables, county-level demographics, and hospital infrastructure variables, as well as characteristics of the receiving hospital. Since the hospital allocation is conditioned on patient severity, it is difficult to interpret the coefficients for characteristics of the receiving hospitals. One interpretation is that they are simply controls for the patient's county and severity.

The next specification includes controls for TIME_AT_SCENE and TIME_TO_HOSP. The TIME_TO_HOSP variable can be thought of as a control for the distance from the patient to the hospital, although we show later that the hospital allocation (and thus expected travel time) are conditioned on the patient's severity. The TIME_AT_SCENE is more difficult to interpret. It might represent the extra time required to administer treatments that are only available on some ambulances, in which case longer TIME_AT_SCENE should be associated with longer TIME_TO_SCENE, since we expect a longer wait for the scarce resource of a better ambulance. It might also represent some features of the patient's location, such as the presence of elevators or stairs in a high-rise building. High-rises might be located closer to hospitals. However, when the largest counties are excluded, there are probably fewer high-rises in the data set.

The last specification considers only counties who changed their 911 system during the year. Since a fixed effect is included for each county, the coefficients on the 911 dummies can be interpreted as differences in the mean response time as a result of the change. Of course, all time-invariant variables are dropped from this regression, and in addition, several other control variables were dropped due to the small number of observations. Since an alternative explanation for any findings in the first three specifications is that unobserved differences in counties drive the results, our findings for within-county changes are particularly interesting despite the limited size of the data set that considers such changes.

Consider now the results of our analysis. The first result is that TIME_TO_SCENE is lower in counties with no 911 or Basic 911 than counties with E911. In the base specification, counties with no 911 are about 10 percent slower than counties with E911, while counties with Basic are approximately 8 percent slower than counties with E911. The magnitudes vary somewhat in different specifications, and the result for no 911 is not always significantly different from zero. Nonetheless, the signs of the coefficients are robust to a variety of specifications. When interpreting these results, it is of course important to observe the caveat that results may be driven by unobserved differences between counties, such as the distribution of residences relative to hospitals. However, as shown earlier in figure 4.3, many adjacent counties in similar geographical areas have different 911 systems, and further, when the four largest counties are excluded, the counties are fairly comparable in terms of demographics. Of course, controls are included for several important demographic variables as well as the number of hospitals per mile in the county (which decreases response time, as expected).

In order to provide further evidence about the robustness of the results, we consider the final specification, which includes only counties that changed during the year. The county that changed from Basic to Enhanced 911 saw a 14 percent decrease in its TIME_TO_SCENE, while the counties that changed from no 911 to Basic saw a decrease that is not statistically significant. The weaker results about changes from no 911 to Basic 911 may reflect the fact that moving to a centralized 911 system *without* automated address-finding technology may have ambiguous results, especially in the short run. At a minimum, the system may require some learning-by-doing before call takers in a new 911 system are able to gather correct address information for a large area.

We also find that the emergency response system appears to respond to the severity of the patient's symptoms: patients with a higher Glasgow score have somewhat higher TIME_TO_SCENE, although this result is not statistically significant. We do not, however, see differences in the TIME_TO_SCENE for different categories of insurance (Medicare is the comparison group) or for different ages, with the exceptions that Medicaid patients and younger patients tend to have faster response times.

County-level demographics are also correlated with TIME_TO_SCENE. When the largest counties are included, counties with large populations and high densities have faster response times; once the large counties are excluded, the results are reversed. In all cases, higher income is associated with faster response times.

Table 4.8 analyzes the determinants of TIME_AT_SCENE, following the same set of specifications as in table 4.7. TIME_AT_SCENE is negatively related to both TIME_TO_SCENE and TIME_TO_HOSP. It is increasing in the level of 911, and it is longer for more severe patients. TIME_AT_SCENE is also longer for highly populated counties and especially in those with high crime rates, while it is lower in densely populated, high-income, and high-expenditure counties. A full interpretation of these results would require further investigation into the services provided by ambulances and how they vary with TIME_AT_SCENE. For example, if longer TIME_AT_SCENE is positively correlated with more services, we can interpret the results as saying that more ambulance services are provided in counties with higher levels of 911. This interpretation seems inconsistent with the results on income and expenditures, however.

Table 4.9 considers the determinants of TIME_TO_HOSP. Again, the specifications parallel tables 4.7 and 4.8. We find that, in all specifications, counties with higher levels of 911 have shorter TIME_TO_HOSP. Again, this result holds controlling for demographic factors as well as for the number of hospitals per mile (which decreases TIME_TO_HOSP

Table 4.8 **Time-at-Scene Equation**

	Dependent Variable = L TIME_AT_SCENE			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
Time controls				
L TIME_TO_SCENE		−0.12301	−0.1574	−0.25261
		(0.00611)	(0.00777)	(0.02734)
L TIME_TO_HOSP		−0.04943	−0.05542	−0.10568
		(0.00529)	(0.00669)	(0.02515)
911 level				
NO 911	−0.18644	−0.16716	−0.18038	−0.0343
	(0.01522)	(0.01501)	(0.01665)	(0.07951)
BASIC 911	−0.09558	−0.08014	−0.07043	0.11722
	(0.01202)	(0.01186)	(0.01271)	(0.0485)
Patient characteristics				
MALE	−0.03912	−0.03228	−0.03712	−0.03224
	(0.00744)	(0.00733)	(0.00932)	(0.03216)
AGE	0.00536	0.00691	0.00397	0.00001
	(0.00184)	(0.00181)	(0.00254)	(0.00857)
AGE_SQUARED	−0.00001	−0.00003	−0.00001	0.00002
	(0.00001)	(0.00001)	(0.00002)	(0.00007)
CARDIAC ARREST	0.02266	−0.00199	0.06571	0.13014
	(0.01602)	(0.01581)	(0.0359)	(0.13162)
DEFIBRILLATE	0.03347	0.03949	0.0247	0.06299
	(0.00758)	(0.00747)	(0.00959)	(0.03616)
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown)				
GLASGOW 0	2.17322	2.45456	2.54128	
	(0.1807)	(0.1783)	(0.22585)	
GLASGOW 3	2.45973	2.74229	2.75759	0.17614
	(0.18206)	(0.17964)	(0.22742)	(0.19364)
GLASGOW 4–9	2.30703	2.58851	2.60049	−0.26967
	(0.18212)	(0.1797)	(0.22805)	(0.20899)
GLASGOW 10–12	2.20594	2.5016	2.55148	−0.03566
	(0.18177)	(0.17938)	(0.22728)	(0.19633)
GLASGOW 13–14	2.19037	2.48132	2.54956	−0.15936
	(0.18029)	(0.17792)	(0.2255)	(0.1574)
GLASGOW 15	2.17405	2.47202	2.51962	−0.10864
	(0.17975)	(0.17741)	(0.22466)	(0.13614)
Insurance status (excluded category = Medicare)				
MEDICAID	0.00908	−0.00695	0.00054	−0.00165
	(0.01854)	(0.01827)	(0.02357)	(0.07775)
PRIVATE	−0.02495	−0.023	−0.0457	−0.10748
	(0.01171)	(0.01153)	(0.01489)	(0.04931)
SELF PAY	−0.00607	−0.00293	−0.01054	−0.51433
	(0.03419)	(0.03368)	(0.03861)	(0.22833)

(continued)

Table 4.8 (continued)

	Dependent Variable = L TIME_AT_SCENE			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
OTHER	0.01131	0.01001	−0.00877	−0.10236
	(0.02051)	(0.0202)	(0.02758)	(0.07877)
County hospital infrastructure				
CERT. TRAUM CENTER	−0.08111	−0.05414	−0.11849	
	(0.01321)	(0.01305)	(0.01979)	
L HOSP PER SQ. MILE	0.12706	0.10232	0.08358	
	(0.01066)	(0.01054)	(0.01423)	
L COUNTY CARDIAC PATIENTS	−0.10168	−0.10644	−0.104	
	(0.01055)	(0.0104)	(0.01187)	
County demographics				
L POPULATION	0.43383	0.42261	0.37463	
	(0.02746)	(0.02706)	(0.02935)	
DENSITY	−0.07099	−0.06761	−0.03212	
	(0.00493)	(0.00486)	(0.04967)	
L INCOME PER CAP	−0.19859	−0.20712	−0.13367	
	(0.03314)	(0.03275)	(0.04764)	
VCRIMERATE	35.18246	36.32172	52.4423	
	(3.80783)	(3.75116)	(4.71698)	
L POLICE EXP	−0.17784	−0.16911	−0.18477	
	(0.02007)	(0.01978)	(0.02205)	
L HEALTH EXP	−0.01733	−0.01811	−0.01583	
	(0.00378)	(0.00373)	(0.00406)	
Hospital characteristics				
URGENT CARE CENTER	−0.03078	−0.0354	−0.07251	
	(0.0102)	(0.01005)	(0.014)	
CATH LAB	0.0825	0.08175	0.09871	0.13936
	(0.01062)	(0.01047)	(0.01386)	(0.05607)
OPENHEART FAC	−0.07375	−0.0707	−0.11318	
	(0.01114)	(0.01098)	(0.0188)	
TRAUMA CENTER LEVEL	0.0035	−0.0072	−0.00458	
	(0.01059)	(0.01044)	(0.01889)	
EMERGENCY ROOM VOLUME	0.0008	0.00087	0.00174	0.13112
	(0.00038)	(0.00038)	(0.00054)	(0.05946)
HOSPITAL DOCTORS	−0.00019	−0.00017	−0.00113	−0.12205
	(0.00023)	(0.00022)	(0.00052)	(0.05052)
HOSPITAL RESIDENTS	0.00027	0.00033	0.00167	−0.02503
	(0.00006)	(0.00006)	(0.00037)	(0.00954)
Constant				3.20254
				(0.33705)
Observations	24,664.0000	24,664.0000	16,477.0000	1,635.0000
R-squared	0.7040	0.7170	0.7170	

Table 4.9 **Time-to-Hospital Equation**

	Dependent Variable = L TIME_TO_HOSPITAL			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
Time controls				
L TIME_TO_SCENE		0.44086	0.47724	0.44745
		(0.00686)	(0.00837)	(0.0253)
L TIME_AT_SCENE		−0.07159	−0.07504	−0.10268
		(0.00765)	(0.00906)	(0.02444)
911 level				
NO 911	0.15649	0.10178	0.10605	0.09964
	(0.01963)	(0.0181)	(0.01943)	(0.07834)
BASIC 911	0.12466	0.08459	0.08718	0.07311
	(0.01551)	(0.01427)	(0.01479)	(0.04786)
Patient characteristics				
MALE	0.04784	0.02903	0.02066	0.03623
	(0.00959)	(0.00882)	(0.01085)	(0.0317)
AGE	0.01282	0.00992	0.00874	0.00106
	(0.00237)	(0.00218)	(0.00295)	(0.00845)
AGE_SQUARED	−0.00011	−0.00009	−0.00008	−0.00002
	(0.00002)	(0.00002)	(0.00002)	(0.00006)
CARDIAC ARREST	−0.18747	−0.13073	−0.13198	−0.00151
	(0.02066)	(0.019)	(0.04177)	(0.03567)
DEFIBRILLATE	0.03532	0.0224	0.03799	−0.21201
	(0.00978)	(0.009)	(0.01115)	(0.07646)
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown)				
GLASGOW 0	1.6977	1.14576	1.15614	−0.34525
	(0.23308)	(0.21527)	(0.26366)	(0.19073)
GLASGOW 3	1.65137	1.10733	1.11887	−0.41187
	(0.23483)	(0.21709)	(0.26567)	(0.20586)
GLASGOW 4–9	1.57387	1.00906	1.07255	−0.0466
	(0.23491)	(0.21707)	(0.26628)	(0.19352)
GLASGOW 10–12	1.73412	1.13965	1.14773	−0.30685
	(0.23446)	(0.2166)	(0.26532)	(0.15502)
GLASGOW 13–14	1.73479	1.1562	1.16163	−0.04845
	(0.23255)	(0.21483)	(0.26326)	(0.13422)
GLASGOW 15	1.8255	1.23666	1.2426	−0.10085
	(0.23185)	(0.21419)	(0.26224)	(0.12976)
Insurance status (excluded category = Medicare)				
MEDICAID	−0.1092	−0.07043	−0.07683	−0.07046
	(0.02391)	(0.02198)	(0.02741)	(0.04865)
PRIVATE	0.04206	0.04077	0.04224	0.27275
	(0.0151)	(0.01388)	(0.01732)	(0.22532)
SELF PAY	0.08497	0.08834	0.11029	−0.08129
	(0.04409)	(0.04053)	(0.04492)	(0.07766)

(*continued*)

Table 4.9 (continued)

	Dependent Variable = L TIME_TO_HOSPITAL			
	Base Regression (OLS)	Time Controls (OLS)	Excluding 4 Largest Counties (OLS)	Only Counties with 911 Level Changes (Fixed Effects)
OTHER	0.01589	0.02416	−0.00221	
	(0.02645)	(0.02431)	(0.03209)	
County hospital infrastructure				
CERT. TRAUM CENTER	0.15252	0.07711	0.05555	
	(0.01704)	(0.0157)	(0.02305)	
L HOSP PER SQ. MILE	−0.18727	−0.12268	−0.09829	
	(0.01374)	(0.01269)	(0.01656)	
L COUNTY CARDIAC PATIENTS	0.0448	0.06252	0.09978	
	(0.01361)	(0.01254)	(0.01382)	
County demographics				
L POPULATION	0.00389	0.07585	0.06252	
	(0.03542)	(0.03272)	(0.03432)	
DENSITY	−0.01008	−0.02905	0.18259	
	(0.00636)	(0.00587)	(0.05779)	
L INCOME PER CAP	−0.44325	−0.5054	−0.46603	
	(0.04275)	(0.03932)	(0.05533)	
VCRIMERATE	5.65587	5.09363	2.34351	
	(4.91153)	(4.52272)	(5.50937)	
L POLICE EXP	0.01922	−0.02139	−0.08667	
	(0.02589)	(0.02383)	(0.0257)	
L HEALTH EXP	0.01653	0.02102	0.02104	
	(0.00488)	(0.00449)	(0.00473)	
Hospital characteristics				
URGENT CARE CENTER	−0.00081	0.0134	0.00072	0.16509
	(0.01316)	(0.0121)	(0.01631)	(0.05522)
CATH LAB	0.06756	0.08813	0.10653	
	(0.0137)	(0.01261)	(0.01613)	
OPENHEART FAC	−0.00712	−0.02461	−0.01003	
	(0.01437)	(0.01322)	(0.0219)	
TRAUMA CENTER LEVEL	−0.05772	−0.02935	−0.05217	−0.02545
	(0.01366)	(0.01256)	(0.02198)	(0.0587)
EMERGENCY ROOM VOLUME	0.00025	0.00012	−0.00144	0.02418
	(0.00049)	(0.00045)	(0.00063)	(0.04989)
HOSPITAL DOCTORS	0.00126	0.00138	0.00244	0.01174
	(0.00029)	(0.00027)	(0.00061)	(0.00942)
HOSPITAL RESIDENTS	0.00073	0.00065	0.00135	1.67951
	(0.00008)	(0.00008)	(0.00043)	(0.33885)
Constant				3.20254
				(0.33705)
Observations	24,664.000	24,664.000	16,477.000	1,635.000
R-squared	0.704	0.717	0.717	

sharply), and also when large counties are excluded and when only within-county changes are considered (although the result for changes from no 911 to Basic 911 are weakened substantially in the within-county specification). In future work, we hope to consider interactions between Enhanced 911 and other allocation variables.

We find that travel times are longer for patients allocated to hospitals with a large number of doctors, residents (indicating teaching hospitals), and with cardiac catheterization laboratories. Thus, we have some evidence that patients with more severe indications are transported to higher quality, but more distant, hospitals. This is consistent with the official protocols for patient allocation for Pennsylvania counties: According to the protocols, the most severe indications are to be transported to hospitals with appropriate capabilities, while less severe indications are to be transported to the nearest hospital.

Also in contrast to the results on TIME_TO_SCENE, we see that the patient insurance mix affects the time it takes to transport patients to the hospital. Relative to Medicare patients (the majority of our sample), Medicaid patients have shorter transport times. This may partly reflect the fact that Medicaid patients are more likely to reside in the urban areas of their counties (though rural areas of Pennsylvania have Medicaid patients as well). It may also reflect a lack of patient choice: Better-insured patients may travel longer to get to a better hospital. Privately insured patients tend to travel longer, although this result is somewhat weaker. In addition to the possibility that these patients choose to travel to better hospitals, an alternative explanation is that their insurance policies make some hospitals more desirable than others. For example, patients may anticipate financial penalties from receiving treatment from a hospital that is not affiliated with their health plan.

Having characterized the "intermediate inputs" to patient outcomes, we can now turn to assess the impact of 911 and hospital type on the probability of dying from a cardiac incident requiring ambulance transportation (fig. 4.4 and table 4.10). We begin with a simple reduced-form regression of mortality on 911 as well as the controls from tables 4.7–4.9. We do not find strong effects of 911 on mortality. There are several potential explanations for this result. One is that mortality rates are fairly low, and there are simply not enough deaths in the no 911 and Basic 911 counties to uncover the effects. Another possibility is that unobserved heterogeneity across counties confounds the effects of response time (although our results are robust to a variety of county-level control variables). We do see that mortality is decreasing in the number of hospitals per mile and the income of a county, while it is increasing in the crime rate and police expenditures.

In all of the specifications, we find that older patients are less likely to die (they may also be more likely to use ambulance services in less severe

Table 4.10 **Mortality Equation**

	Dependent Variable = Death Outcome Dummy		
	Reduced Form (OLS)	Base Regression (OLS)	Base Regression (IV)[a]
Time outcomes			
L TIME_TO_SCENE		0.00535	0.03122
		(0.00268)	(0.01974)
L TIME_AT_SCENE		0.01266	0.04073
		(0.00275)	(0.01434)
L TIME_TO_HOSP		−0.00690	0.01896
		(0.00228)	(0.01187)
911 level			
NO 911	−0.00104		
	(0.00658)		
BASIC 911	0.00030		
	(0.00520)		
Patient characteristics			
MALE	0.00529	0.00591	0.00479
	(0.00322)	(0.00322)	(0.00329)
AGE	−0.00281	−0.00276	−0.00352
	(0.00080)	(0.00080)	(0.00083)
AGE_SQUARED	0.00003	0.00003	0.00004
	(6.06 e-6)	(6.05 e-6)	(6.26 e-6)
CARDIAC ARREST	0.01709	0.01271	0.02566
	(0.00693)	(0.00627)	(0.00718)
DEFIBRILLATE	0.02500	0.02441	0.02149
	(0.00328)	(0.00326)	(0.00342)
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown and default)			
GLASGOW 3	0.31672	0.31605	0.30487
	(0.01177)	(0.01146)	(0.01249)
GLASGOW 4–9	0.19542	0.19380	0.19219
	(0.01485)	(0.01419)	(0.01536)
GLASGOW 10–12	0.11793	0.11838	0.11426
	(0.01423)	(0.01419)	(0.01449)
GLASGOW 13–14	0.02183	0.02261	0.01969
	(0.01077)	(0.01071)	(0.01090)
GLASGOW 15	−0.01625	−0.01459	−0.02021
	(0.00769)	(0.00762)	(0.00783)
Insurance status (excluded category = Medicare)			
MEDICAID	0.00943	0.00782	0.01291
	(0.00802)	(0.00800)	(0.00818)
PRIVATE	0.01071	0.01128	0.01137
	(0.00507)	(0.00505)	(0.00513)
SELF PAY	0.01425	0.01500	0.01194
	(0.01479)	(0.01473)	(0.01498)
OTHER	0.00219	−0.00022	0.00156
	(0.00887)	(0.00877)	(0.00886)

Table 4.10 (continued)

	Dependent Variable = Death Outcome Dummy		
	Reduced Form (OLS)	Base Regression (OLS)	Base Regression (IV)[a]
County hospital infrastructure			
CERT. TRAUM CNTR	0.00378		
	(0.00572)		
L HOSP PER SQ. MILE	−0.00729		
	(0.00461)		
L COUNTY CARDIAC PATIENTS	0.00499		
	(0.00457)		
County demographics			
L POPULATION	−0.00905		
	(0.01188)		
DENSITY	−0.00348		
	(0.00213)		
L INCOME PER CAP	−0.22546		
	(0.01434)		
VCRIMERATE	2.12906		
	(1.64770)		
L POLICE EXP	0.01159		
	(0.00869)		
L HEALTH EXP	−0.00039		
	(0.00164)		
Hospital characteristics			
URGENT CARE CENTER	0.01411	0.01818	0.01782
	(0.00441)	(0.00399)	(0.00428)
CATH LAB	−0.00171	−0.00118	−0.00071
	(0.00460)	(0.00394)	(0.00441)
OPENHEART FAC	−0.00320	0.01818	0.00157
	(0.00482)	(0.00443)	(0.00469)
TRAUMA CENTER LEVEL	0.00726	0.00872	0.01215
	(0.00458)	(0.00399)	(0.00404)
EMERGENCY ROOM	0.00023	0.00033	0.00447
VOLUME	(0.00458)	(0.00015)	(0.00404)
HOSPITAL DOCTORS	−3.46 E-06	0.00003	0.00003
	(0.00098)	(0.00009)	(0.00009)
HOSPITAL RESIDENTS	−0.00005	−0.00008	−0.00010
	(0.00003)	(0.00003)	(0.00002)
Constant	0.04104	−0.00302	−0.20416
	(0.07819)	(0.03106)	(0.07180)
Observations	24,664.000	24,664.000	16,477.000
R-squared	0.107	0.092	

[a]Instruments: NO 911, BASIC 911, CERT. TRAUM CNTR, HOSP PER SQ. MILE, L POPULATION, DENSITY, L INCOME PER CAP, VCRIMERATE, POLICE EXP, AND HEALTH EXP.

situations), while patients for whom cardiac arrest and defibrillation are reported are more likely to die. Likewise, we see a very strong effect of severity as measured by the Glasgow score: Sicker patients are significantly more likely to die than patients with less severe symptoms. Privately insured patients are more likely to die than Medicare patients.

The second and third specifications consider the effects of response time and patient characteristics on mortality. We have already shown that response time varies with the severity of the patient as well as with the kind of hospital to which the patient will eventually be admitted. Thus, it will be somewhat difficult to interpret the effects of the response time variables in the reduced-form mortality regression. We then propose a preliminary strategy for instrumental variables: We use county-level characteristics, and in particular the level of 911, as instruments for response time. We have already established that such characteristics affect the response time; it remains to argue that the level of 911 is uncorrelated with the unexplained variation in patient mortality (when patient-specific variables are included as controls in the regression). Our approach excludes all county-level demographic information from the regression; in future work, it may be possible to include zip-code-level demographic data to capture any heterogeneity that might have been correlated with excluded county-level demographics.

Our instrumental variables results, while preliminary in nature, are suggestive. They show that shorter response times reduce the probability of death. The main coefficient that changes in sign as a result of the instrumental variables approach is the coefficient on TIME_TO_HOSP. It is not surprising that the coefficient changes in sign, since it is most sensitive to the severity of individual patients (in particular, patients with nonurgent symptoms are transported to the hospital without lights and sirens). It is interesting to note that the instrumental variables strategy is successful despite the fact that higher levels of 911 are (unconditionally) correlated with both lower response times and higher average mortality rates.

We do not attempt an instrumental variables strategy for the technology of the hospital, though this is a potential area for future work. In our reduced-form specification, it is difficult to separate out the potentially beneficial effect of going to a better hospital from the effect due to the differential allocation of more severely ill patients and nonemergency patients to better hospitals.

4.6 The Role of Emergency Response Systems in Allocating Patients to Hospitals

As described in sections 4.1 and 4.2, the prehospital system plays an important role in allocating patients to hospitals. However, one of the most critical factors in determining a patient's allocation is the simple

Table 4.11 **Distribution of In-Hospital Emergency and Cardiac Technologies**

	In-Hospital Technology			Certified County Trauma Center
	Cath Lab	Open Heart Surgery Facility	Urgent Care Center	
Total share of patients allocated to hospital with technology	0.6703	0.2940	0.2170	0.1983
Share of patients living in counties with at least one hospital with technology	0.8243	0.6141	0.6055	0.5097
Conditional share of patients allocated to hospitals with technology	0.8131	0.4787	0.3586	0.3892

availability of a hospital with advanced technologies in his or her county. Table 4.11 shows that 80 percent of patients in our data set had within-county access to hospitals with cardiac catheterization laboratories, while only half had access to a certified county trauma center. Conditional on access to a hospital with a cardiac catheterization laboratory, approximately 80 percent of patients were allocated to such a hospital. The conditional probabilities of being allocated to hospitals with other features is substantially lower for the cardiac patients in our data set. Table 4.11 illustrates that, as opposed to the more common situation where the primary barrier to access derives from a patient's insurance status, a patient's geographical location may be the main determinant of whether a patient receives treatment in a hospital with specialized cardiac care or emergency services. Patients in poorer and less-populated regions may not receive access to such care.

In table 4.12, we explore further the factors that affect allocation of patients to hospitals, conditional on availability of the technology. The main result in this table is that for cardiac catheterization laboratories, the level of 911 significantly increases the probability of being admitted to a high-technology hospital (this result is robust to including controls for the *number* of hospitals in the county with cardiac catheterization laboratories). This is consistent with an important allocative role played by 911 centers.

We further find that, excluding the largest counties, patients with very severe and very mild indications were most likely to go to hospitals with high levels of technology. The result for less-severe patients could be due to the use of ambulances for cases that are more elective in nature, since patients may be reporting emergencies in order to have access to the ambulances for basic transportation. Patient insurance status further affects the hospital allocation decision. We find that privately insured patients are

Table 4.12 Patient Allocation Equation

	Dependent Variable = Allocated to Hospital with Cath Lab (Conditional on at Least One Cath Lab Hospital within County)	
	Cath Lab (Probit)	Excluding 4 Largest Counties
911 level		
NO 911	−1.00733	−1.16728
	(0.06863)	(0.07387)
BASIC 911	−0.28051	−0.46803
	(0.03050)	(0.03800)
Patient characteristics		
MALE	−0.03312	−0.00646
	(0.02189)	(0.02860)
AGE	−0.00412	0.00091
	(0.00562)	(0.00795)
AGE_SQUARED	−1.85 E-06	−0.00005
	(0.00004)	(0.00006)
CARDIAC ARREST	0.58741	−0.08791
	(0.05086)	(0.10797)
DEFIBRILLATE	−0.01392	0.01356
	(0.02256)	(0.03001)
Glasgow trauma score (15 = least severe; 3 = most severe; 0 = unknown and default)		
GLASGOW 3	−0.84533	−0.37461
	(0.08582)	(0.13860)
GLASGOW 4–9	−0.47575	−0.67050
	(0.10140)	(0.14290)
GLASGOW 10–12	−0.32729	−0.53630
	(0.10122)	(0.13994)
GLASGOW 13–14	−0.37244	−0.41117
	(0.07923)	(0.10938)
GLASGOW 15	−0.32983	−0.38695
	(0.06085)	(0.08417)
Insurance status (excluded category = Medicare)		
MEDICAID	0.18089	0.171265
	(0.05760)	(0.07802)
PRIVATE	0.04216	−0.00565
	(0.03485)	(0.04621)
SELF PAY	0.11544	0.27962
	(0.09776)	(0.10839)
OTHER	−0.22751	−0.26058
	(0.05842)	(0.08373)
County hospital infrastructure		
CERT. TRAUM CENTER	−0.19506	−0.66830
	(0.04109)	(0.05677)
L HOSP PER SQ. MILE	−0.15402	−1.15404
	(0.03673)	(0.06159)
L COUNTY CARDIAC PATIENTS	−0.09191	−0.13927
	(0.04060)	(0.05710)

Table 4.12 (continued)

	Dependent Variable = Allocated to Hospital with Cath Lab (Conditional on at Least One Cath Lab Hospital Within County)	
	Cath Lab (Probit)	Excluding 4 Largest Counties
County demographics		
L POPULATION	−2.34760	−2.67815
	(0.13631)	(0.15202)
DENSITY	−0.04246	1.72541
	(0.01450)	(0.18301)
L INCOME PER CAP	−0.39597	0.15092
	(0.10642)	(0.15613)
VCRIMERATE	−134.69580	−105.51410
	(14.0461)	(15.50315)
L POLICE EXP	1.85107	2.08144
	(0.10056)	(0.10894)
Constant	11.41237	5.40536
	(0.74178)	(0.86296)
Observations	20,333.000	12,146.000
Log-likelihood	−9,089.698	−5,336.958

allocated in a similar fashion to Medicare patients. However, Medicaid and self-pay patients are more likely to be treated in high-tech hospitals. This result, which is somewhat puzzling, may be due to the fact that hospitals are often located in poor areas; further, this result may be spurious, as almost all patients are insured either privately or through Medicare.

Table 4.12 also shows that the probability of being admitted to a hospital with a cardiac catheterization laboratory is *decreasing* in the number of hospitals per square mile. We interpret this result as a consequence of the allocation protocols: Patients are generally taken to the closest hospital that meets general criteria, and areas with more hospitals per square mile may have a number of hospitals with low levels of technology. In contrast, many counties have only two or three hospitals, one of which has a cardiac catheterization laboratory.

Our final empirical exercise considers directly the incentives of hospitals to adopt higher levels of technology. Identifying the role that hospital characteristics play in determining the allocation of ambulance patients is in many ways similar to a study of a differentiated goods demand system, in which hospitals compete in the marketplace for patients on the basis of geography and characteristics. However, these two settings also differ in some respects; in particular, while hospitals will presumably have incentives to attract some ambulance patients, a given hospital may want to

Table 4.13 Hospital Market Share Equation (excludes four largest counties)

	Dependent Variable = L Hospital Market Share
Individual hospital characteristics	
URGENT CARE CENTER	0.6070
	(0.2911)
CATH LAB	0.5998
	(0.2717)
OPENHEART FAC	0.1522
	(0.3994)
TRAUMA CENTER LEVEL	0.6626
	(0.3233)
HOSPITAL DOCTORS	0.0163
	(0.0122)
HOSPITAL RESIDENTS	0.0008
	(0.0102)
Intensity of rival hospital competition	
NO. OF HOSPITALS	−1.0527
	(0.1432)
AVERAGE URGENT CARE CENTER	−0.3947
	(0.3850)
AVERAGE CATH LAB	−0.6712
	(0.3689)
AVERAGE OPENHEART FAC	−0.1427
	(0.5958)
AVERAGE TRAUMA CENTER LEVEL	−0.6226
	(0.3575)
AVERAGE HOSPITAL DOCTORS	−0.0213
	(0.0157)
AVERAGE HOSPITAL RESIDENTS	0.0084
	(0.0138)
Constant	−0.1513
	(0.7788)
Observations	101.0000
R-squared	0.5419

deter particular types of patients (the uninsured or patients who are hard-to-treat but do not generate significant income). While these distributional questions are extremely interesting, the present analysis will focus on the sensitivity of the overall patient share to particular hospital investments.

Table 4.13 presents results that relate the proportion of a county's patients in the data set who are allocated to a given hospital, SHARE, to the characteristics of that hospital as well as the characteristics of other hospitals in the county. First, and not surprisingly, the market share of a given hospital is declining in the total number of hospitals present in a given county. Our more interesting results are derived from our analysis of the specific features of hospitals that seem to affect this market share.

In particular, simple measures of the overall size of the hospital—the total number of physicians, the total number of hospital beds—are uncorrelated with the hospital market share. In contrast, specific technological investments (such as cardiac catheterization laboratories and the rating of the emergency room) are correlated with the overall market share. Since allocation does appear to respond to technology investment, we conclude that the interaction between the prehospital system and technology adoption should be considered in analyses of the incentives for investment by hospitals.

One important caveat to our interpretation of table 4.13 is that our results do not necessarily imply that if a given hospital increased its technology, it would increase its market share. If our sample contains a hospital characterized by higher than average quality, larger numbers of consumers would use that hospital. The large market share could increase the incentives of the hospital to adopt technology; or it could be that technology is an integral part of maintaining high overall quality. In either case, a low-quality hospital that adopted sophisticated technology would not necessarily increase its market share.

It is also possible to investigate how the sensitivity of market share to hospital characteristics might depend on the type of prehospital emergency response system available in a given county. However, in our preliminary analysis of this data set, we have not found a robust interaction effect.

4.7 Conclusions

From our analysis in this paper, we draw several conclusions that we hope will have an impact on future research. First, our results highlight that emergency response systems play two distinct roles: productive and allocative. It therefore seems important to consider the potential bias that arises in studies that take allocation as exogenous or that do not account for the heterogeneity in county mortality rates that are induced by higher levels of prehospital care (such as lower response times or on-the-scene defibrillation). Further, the incentives generated by the prehospital system need to be taken into account when regulators and insurance companies consider creating additional incentives for hospitals. Our analysis highlights one particularly important feature of the prehospital system: It interacts with the incentives of hospitals to adopt new technologies and maintain highly rated emergency facilities.

Our reduced-form results can be extended to provide a more structural understanding of the interaction between the prehospital infrastructure and hospital competition. For example, we find that patients are allocated by the prehospital system according to their severity and the technology that a hospital employs (see tables 4.12 and 4.13); it is left to future work to evaluate whether these allocative effects are reflected in terms of strategic investment behavior by hospitals.

Examining 911 services also provides a glimpse into the challenges (and types of data) that are necessary for accurate measurement of productivity in the service sector. In particular, service-sector productivity measurement must incorporate the quality of the activity (such as timeliness) as well as whether the services received by the customer are responsive to his or her idiosyncratic characteristics (in this case, different patients experience different diagnoses and different degrees of severity of illness). By developing and analyzing a novel data set, we are able to provide evidence about both of these factors (in this case, timely response and allocation of patients to appropriate hospitals). Of course, we are not the first to evaluate multiple attributes of a service provided. However, our analysis is further able to connect these measures of quality to a well-defined overall service outcome measure—mortality.

Finally, a more careful understanding of the production structure of services is an important first step toward analyzing the nature of strategic interactions between service providers. For example, the extent to which firms can influence their market share through overinvestment in technology and wasteful business-stealing activities will depend in part on the importance of customized service and the quality of the match between consumer characteristics and firm investments. These considerations might have implications for the regulation and management of service industries.

References

Bonnin, M. J., P. E. Pepe, and P. S. Clark. 1993. Survival in the Elderly after Out-of-Hospital Cardiac Arrest. *Critical Care Medicine* 21 (11): 1645–51.

Bresnahan, Timothy F., and Robert J. Gordon, eds. 1997. *The Economics of New Goods.* NBER Studies in Income and Wealth, vol. 58. Chicago: University of Chicago Press.

Brown, E., and J. Sindelar. 1993. The Emergent Problem of Ambulance Misuse. *Annals of Emergency Medicine* 22 (4): 646–50.

Cummins, R. O., J. P. Ornato, W. H. Thies, and P. E. Pepe. 1991. Improving Survival from Sudden Cardiac Arrest: The "Chain of Survival" Approach. *Circulation* 83 (5): 1832–47.

Fischer, M., N. J. Fischer, and J. Schuttler. 1997. One-Year Survival after Out-of-Hospital Cardiac Arrest in Bonn City: Outcome Report According to the "Utstein Style." *Resuscitation* 33 (3): 233–43.

Gibson, G. 1977. Measures of Emergency Ambulance Effectiveness: Unmet Need and Inappropriate Use. *Journal of the American College of Emergency Physicians* 6 (9): 389–92.

Griliches, Z. 1994. Productivity, R&D, and the Data Constraint. *American Economic Review* 84 (1): 1–23.

Hoffer, E. 1979. Emergency Medical Services 1979. *New England Journal of Medicine* 301 (20): 1118–21.
Joslyn, S. A., P. R. Pomrehn, and D. D. Brown. 1993. Survival from Out-of-Hospital Cardiac Arrest: Effects of Patient Age and Presence of 911 Emergency Medical Services Phone Access. *American Journal of Emergency Medicine* 11 (3): 200–206.
Larsen, M. P., M. S. Eisenberg, R. O. Cummins, and A. P. Hallstrom. 1993. Predicting Survival from Out-of-Hospital Cardiac Arrest: A Graphic Model. *Annals of Emergency Medicine* 22 (11): 1652–58.
Lewis, R. P., R. R. Lanese, J. M. Stang, T. N. Chirikos, M. D. Keller, and J. V. Warren. 1982. Reduction of Mortality from Prehospital Myocardial Infarction by Prudent Patient Activation of Mobile Coronary Care System. *American Heart Journal* 103 (1): 123–29.
McClellan, M., and J. Newhouse. 1997. The Marginal Cost-Effectiveness of Medical Technology: A Panel Instrumental-Variables Approach. *Journal of Econometrics* 77 (1): 39–64.
Pivetta, Sue. 1995. *The 911 Puzzle: Putting All of the Pieces Together.* Cleveland, Ohio: National Emergency Number Association.
Siler, Kenneth P. 1975. Predicting Demand for Publicly Dispatched Ambulances in a Metropolitan Area. *Health Services Research* 10 (3): 254–63.
Smith, Ken. 1988. The Ambulance Service: Past, Present, and Future. *Practitioner* 232:879–82.
Tresch, D. D., R. Thakur, and R. Hoffman. 1989. Should the Elderly Be Resuscitated Following Out-of-Hospital Cardiac Arrest? *American Journal of Medicine* 86:145–50.
Vogt, W. 1997. Detecting Strategic Behavior in Technology Adoption: The Example of Magnetic Resonance Imaging. Carnegie Mellon University, Pittsburgh, Penn. Mimeograph.
Weston, C. F., R. J. Wilson, and S. D. Jones. 1997. Predicting Survival from Out-of-Hospital Cardiac Arrest: A Multivariate Analysis. *Resuscitation* 34 (1): 27–34.

Comment on Chapters 3 and 4

Catherine Wolfram

McClellan and Staiger

Mark McClellan and Douglas Staiger present a new method for measuring hospital quality and then use their approach to consider quality differences across hospital types. Using information from nearly 4,000 hospitals nationwide, they find that government and for-profit hospitals are lower quality than not-for-profit (heart patients at these hospitals are more likely to die within 90 days of treatment) and that high volume hospitals are higher quality than smaller hospitals. They also perform a more detailed case study of a handful of hospitals in three distinct markets, and they uncover an interesting correlate to their aggregate results. At least in

Catherine Wolfram is assistant professor of economics at Harvard University and a faculty research fellow of the National Bureau of Economic Research.

the three markets they consider, for-profit hospitals did not have higher mortality rates than their not-for-profit competitors, and in one market, a for-profit firm entered by taking over a low-quality hospital, but then raised the hospital's quality level. Their findings could imply that for-profit hospitals are not lower quality (as the national results suggest), but that they selectively enter markets (that is, take over hospitals) where quality is low. Perhaps they even subsequently improve quality levels.

Before discussing McClellan and Staiger's findings, I will comment on their approach to measuring quality differences, as it is novel and affects their results. The authors identify three issues confronted by researchers attempting to assess hospital quality—data availability, the ability to control for the selection of patients across hospitals, and noise. Their study improves on past quality measures but addresses two of the three issues (data and noise) more thoroughly than the third (selection).

The authors point out two shortcomings in the data currently collected by hospitals and health care providers for use in comparing hospital quality. For one thing, many institutions do not systematically collect and disseminate measures of patient outcomes. Secondly, the data that are collected often cannot be used to make meaningful comparisons across organizations, and worse, the convenient comparisons can be grossly misleading. In a particularly poignant example, the authors consider data that records each patient's status at the time he or she is discharged from the hospital. If we assume (for expositional purposes) that all patients undergoing a procedure performed in a hospital get worse over time, then hospitals or insurance plans that discharge their patients *earlier* would look *better* (i.e., they would report data on fewer sick patients) even if being discharged early reduced the patient's chances of surviving 90 days after the procedure.

McClellan and Staiger use Medicare records on all patients hospitalized for one of two heart-related illnesses between 1984 and 1991. Overall, their data include over one-half million observations. They avoid biases based on the length of a patient's hospital stay because their data set follows every patient through the 90th day following the *initial* hospitalization and records whether or not the patient dies. They then aggregate observations on patients to develop hospital-level mortality rates.

One advantage to using mortality rates as a measure of quality is that deaths are easy outcomes to measure consistently across hospitals. Also, if mortality rates are systematically different across hospitals, presumably few people would willingly choose a low-quality hospital that was equivalent to other hospitals on other dimensions (e.g., cost or proximity). Nonetheless, by comparing hospitals only based on mortality rates, the authors do not capture the full range of attributes patients and their families are likely to value. For instance, McClellan and Staiger find that smaller hospitals generally have higher mortality rates (confirming previous research).

If smaller hospitals provide other attributes that patients and their families value, such as more provider time, it is reasonable to think that rational, fully informed patients would choose a hospital with "lower quality" as measured by McClellan and Staiger. Since the authors are only capturing one dimension of quality, it may be unwise to use their results to make policy prescriptions, for instance, about the optimal hospital size.

A second problem confronting most hospital quality measures that rely on patient outcomes is that the initial allocation of patients to hospitals is not random. In particular, measured quality differences are likely to underrepresent true differences if sicker patients tend to go to (or be taken to) better hospitals. McClellan and Staiger argue that by considering heart disease, they are minimizing the problem since "urgency limits the opportunities for selection across hospitals." Compared to studies of other illnesses, this argument seems valid, though the paper by Athey and Stern in this volume suggests that some selection occurs even among heart patients brought to the hospital in an ambulance. Athey and Stern find evidence suggesting that sicker patients are more likely to be taken to hospitals with cardiac catheterization laboratories or trauma centers. In fact, ambulance operators follow strict protocols when they make decisions on allocating patients and are only allowed to take patients to a hospital other than the nearest one under prespecified conditions. As a result, selection is most likely limited to observables on the hospital type, for instance, whether or not it has a trauma center. Since McClellan and Staiger's main focus is on comparing hospitals by type, any such selection will only be problematic to the extent that, for instance, not-for-profit hospitals are more likely to have trauma centers and so are allocated the sicker patients. Controlling for technological differences across hospitals is probably feasible, particularly in the case studies performed by the authors.

In addition to explicit selection based on a patient's status at hospitalization, different hospitals may be located near patients with different demographic characteristics. In developing their risk-adjusted mortality measures (RAMRs), the authors control for several patient characteristics, including age and gender. Still, it is possible that other attributes of the patients, related to their ability to survive a heart incident, could differ systematically across hospital types. For instance, if government hospitals are more likely to treat veterans and veterans are more likely to smoke than other men of similar ages, McClellan and Staiger's methodology would assign government hospitals higher RAMR measures. It is important to note that the adjustments that McClellan and Staiger make to develop the filtered RAMR will not account for systematic differences across hospitals. In fact, by combining information from different years, they will tend to exacerbate them (by making the differences appear more precisely estimated). Though their measure seems a marked improvement over existing measures in the literature, we should still be a little wary about interpreting differences across their mortality measures as differences in hospital "quality" since hospital selection is still an issue.

The likelihood that a patient survives a heart attack is a function of a number of factors, including the treatment he or she receives at the hospital, his or her age, gender, overall health status, and simple luck. Assuming that the authors could control for all meaningful differences across patients (in other words, leaving the issues addressed in the last paragraph aside), it is still difficult to disentangle the extent to which one hospital provides better care than another from the different patients' luck. For instance, if one hospital admitted 10 heart attack patients over the course of a year and 4 of them died within 90 days and another hospital admitted 10 and 3 of them died, can we conclude that the second hospital provides superior care, or are we simply observing that one more patient at that hospital was lucky? Similarly, if one hospital had 3 out of 10 die and one had 31 out of 100, how do we compare the two hospitals?

The methodology that McClellan and Staiger present in section 3.3 of their paper is designed to minimize the noise in the quality measures (i.e., minimize the role played by luck) and distill information on persistent differences across hospitals. Two main features of their methodology are to adjust for the degrees of freedom by weighting measures by their precision, (so that 31 out of 100 is given more emphasis than 3 out of 10) and to use information from adjoining years and a related illness.

The implications of McClellan and Staiger's case studies—that for-profit hospitals may appear lower quality than not-for-profit because they are choosing to convert low-quality hospitals—is certainly a topic worthy of further research. At times the authors place a very strict interpretation of quality on their filtered RAMR measure as something that is completely under the control of hospital managers and is, for instance, unaffected by local demographics. Taking this interpretation, we would need to look for evidence that for-profit managers choose to convert low-quality hospitals in order to support the implications of their case studies. If we use a less strict interpretation of their quality measures, we could confirm their case study results by finding evidence that for-profit hospitals tend to locate in regions where (age- and gender-adjusted) mortality rates are higher.

It might also be interesting to consider the competitive dynamics between hospitals of different quality levels. For instance, if for-profit hospitals improve the quality of the hospitals they take over, do other hospitals in the local market become better? Along those lines, it would be interesting to see if further research could explain McClellan and Staiger's findings that mortality rates have fallen over time.

Athey and Stern

Susan Athey and Scott Stern have gathered an extensive new data set on 911 systems across the United States and, containing more detail, within

Pennsylvania. In the paper included in this volume, they lay out some of the basic relationships between the level of 911 service a county adopts, ambulance response times within the county, the technology available at the hospitals to which ambulances bring patients, and patients' eventual outcomes. They uncover a number of intriguing patterns, and their results touch on many issues of interest to health care economists, including the role of technology in health outcomes and the extent to which similar patients are allocated to hospitals with different technological capabilities. In these comments, I first give an overview of the paper and discuss some of the individual results, and then I comment on the implications the results have for some broader health care policy and economic questions. While the authors show responsible restraint in drawing conclusions from their results, I will suggest ways in which the results can be pushed to answer relevant policy questions.

At a fundamental level, the authors are concerned with the effect that 911 technologies have on the likelihood that a patient suffering cardiac arrest survives. There are a number of different reasons to believe that 911 would impact patient outcomes, and there are a number of factors potentially at play. For example, the authors point out that the local 911 infrastructure may affect local hospitals' decisions about the type of cardiac care technology in which to invest. Though the possible links between 911 technology levels and patient outcomes are complex, Athey and Stern have gathered enough information to disentangle much of what is going on. Table 4C.1 provides a schematic guide to the types of outcomes and decisions the authors consider. The columns of the table indicate the successive decisions that are made affecting a cardiac patient's chances of survival after calling 911. Each step is delineated in the row labeled "Outcome," the potential outcomes are listed in the row labeled "Possibilities" and several representative factors affecting the possibility that is realized are listed in the row labeled "Factors Affecting Outcome."

As column 1 of table 4C.1 depicts, all U.S. counties have adopted one of three levels of 911 technology (see their article for a description of the different choices). In tables 4.4 and 4.5, Athey and Stern consider covariates with county decisions in, respectively, Pennsylvania and the United States. As 911 service is a local public good, the framework they use is akin to median voter models that others have used to explore local heterogeneity in, for instance, education expenditures. They include factors likely to affect the relative prices of service from the different 911 technology levels (for example, population density, crime rate), income per capita and various demographic factors essentially as proxies for the median voters' tastes (for example, percent of Perot voters in the 1992 election). Their results are not that surprising—indicating, for instance, that more populous, richer counties are more likely to adopt more elaborate 911 systems. The results at the national level in table 4.5 should be interpreted with

Table 4C.1 Decisions Affecting the Treatment of a Cardiac Patient Who Calls 911

Outcome	911 Service Adopted by County (1)	Ambulance Response to Initial Call (2)	Treatment on Premises (3)	Transport to Hospital (4)	Treatment at Hospital (5)
Possibilities	Nothing; basic; E911	Slow to fast	None to defibrillators	Slow (better hospital), fast (closest hospital)	Patient lives or dies
Factors affecting outcomes	County geography; demographics; politics	911 service; county geography	Severity of patient illness	Severity of patient illness; county geography	Type of hospital; prior defibrillation

caution since the authors only have data from 772 counties (out of the universe of 3,000+ counties in the United States), all of which have self-selected by responding to a survey on the local 911 capabilities. The authors point out that the counties that responded to the national survey were more likely to have E911 than the counties in Pennsylvania (where the authors observe the universe of counties), and that selection could be biasing the coefficients reported in table 4.5. For instance, while most counties with E911 respond to the survey, it seems plausible that only counties with high levels of local services (potentially proxied by police expenditures in table 4.5) would have staff with time to respond. Consistent with that, the negative relationship between police expenditures and 911 service level found in table 4.5 is reversed in table 4.4 when the authors consider Pennsylvania.

Next, the authors consider the impact of the level of 911 service on the time it takes an ambulance to reach a patient, the time the ambulance team stays at the scene, and the time it takes the ambulance to drive the patient to the hospital (the relationships represented in table 4C.1 in columns 2, 3, and 4). Regression results are presented in tables 4.7, 4.8, and 4.9, and variable means by county technology level are presented in table 4.6. Consider first the relationship between the county's 911 service level and the time to scene. Here, the direct effect is relatively uncomplicated: All else equal, we would expect that higher levels of 911 technology will permit ambulances to reach patients sooner,[1] so we expect the coefficient on the variable "no 911" to be positive and larger than the positive coefficient on "Basic 911," suggesting that Enhanced 911 is generally quicker. Table 4C.1 indicates one potential problem with uncovering such a relationship across counties. Factors such as the county geography or population density may be correlated both with the benefits of better 911 service and with the speed it would take any ambulance (dispatched from a sophisticated 911 center or not) to reach a patient. That could create a spurious correlation (positive in the example given) between the 911 technology level and the time to scene.

The authors control for some unobserved county heterogeneity by including county-level controls. They also devise individual-level controls by including the variables "time at scene" and "time to hospital" in some specifications in table 4.7. They reason that if it initially takes an ambulance longer to reach a person in a remote location, it would also take longer to get the person to the hospital. The second solution is clever and basically sound, though it could be problematic if, for instance, decisions

1. The authors do point out one complication to the direct effects as I have stated them, suggesting that the ambulances carrying defibrillators may be more common in counties with E911 and that the 911 dispatcher may sacrifice time getting the ambulance to scene in order to find such a vehicle. Such countervailing effects seem much more important in the "time to hospital" and "time at scene" results.

about whether to bring the patient to the closest hospital are affected by the time it takes the ambulance to arrive on the scene. (For instance, if the ambulance gets lost and so takes a long time to arrive at the scene, it might choose to bring the patient to the nearest hospital rather than spending time to drive to a better equipped but more distant hospital.)[2]

The relationship between 911 and both the time the paramedics spend at the scene and the time to hospital are complicated both because the types of omitted variable biases described above might exist and also because there are factors pushing the direct relationship in both directions. For one thing, ambulances often face a trade-off between bringing the patient to the closest hospital and bringing him or her to a more distant but better-equipped facility. If E911 allows ambulances to reach patients quicker initially, the time saved may permit more trips to distant (but better-equipped) hospitals. Such an effect would cause E911 to look less efficient. The coefficients on the 911 service level variables in tables 4.8 and 4.9 do give an indication of the net effect of all factors. So, for instance, the positive coefficients on "no 911" and "Basic 911" suggest that the above-mentioned effect is less important than the fact that E911 helps ambulances navigate more efficiently to the nearest hospital.

Interestingly, the results in table 4.9 suggest that patients transported to better-equipped hospitals (e.g., with cardiac catheterization laboratories) have longer travel times, suggesting that patients are not simply taken to the nearest hospital and that better-equipped hospitals may be receiving sicker patients.[3] Taking off on this result, Athey and Stern analyze the probability that a patient is allocated to a hospital with a cardiac catheterization laboratory as a function of the 911 service level in table 4.12. They document a strong relationship between enhanced 911 and a patient's chances of going to a hospital with a catheterization laboratory (conditional on the county having at least one such hospital). Again, however, those results may reflect unobserved heterogeneity across counties, for example, in the proximity of such labs to the average cardiac patient. Confirming the pattern, though, the authors find that a hospital's level of technological sophistication (for heart patient treatment) affects its share of cardiac care patients brought to it by ambulances.

Athey and Stern note the possibility that 911 technology affects a hospital's decisions about the level of technology in which to invest, but they do not consider it empirically. (This decision is not reflected in table 4C.1,

2. The authors also examine the relationship between 911 level and time to scene using county fixed effects, so that their results are identified off of changes in the time-to-scene in counties that changed the level of 911 service they provide. These results should be interpreted with extreme caution since it appears that only one county changed from Basic 911 to Enhanced 911 and fewer than five changed from no 911 to the basic service.

3. The coefficients on the Glasgow scores—providing direct measures of a patient's sickness—suggest that sicker patients have longer travel times over a certain score range, though the standard errors on the coefficients are bigger than the differences between them.

though would impact the possibilities listed in column 4.) To the extent that 911 service levels have important implications for the way in which patients are allocated to hospitals, this promises to be a fruitful path for future research.

The authors also consider the overall impact of the level of 911 technology on patient mortality rates (see table 4.10). The overall relationship between 911 technology and mortality will reflect the balance of all of the factors documented in columns 2 through 5 of table 4C.1. Unfortunately, they are unable to discern a strong effect of 911 service level on mortality and offer several plausible explanations for that result (among them that mortality rates are extremely noisy, an issue addressed in the McClellan and Staiger paper in this volume). Taking the analysis one step forward (to column 2 in table 4C.1), however, they find that slower ambulance responses are associated with higher mortality rates. In a clever use of their previous findings, they also use the county's 911 service level as an instrument for ambulance transportation times and confirm the relationship between time and mortality that has been documented by previous researchers. (The instrumental variables specifications in table 4.10 also use dummy variables indicating whether or not the county has a catheterization laboratory or a trauma center as instruments. The argument for excluding these from the mortality equation is less clear.) Comparing the two sets of results, it is somewhat puzzling that the timing results are so much stronger than the 911 service levels.

Athey and Stern's work provides new insights on several issues. The authors have pulled together a rich data set with uncommonly detailed measures of the productivity of a particular health care technology. The level of detail they are working with permits them to show that while the relationship between 911 and mortality is muddied by a number of factors, there is a clear relationship between investment in 911 technology and the time to the scene. Their coefficients suggest that having enhanced 911 services reduces the average response times by 5 percent, or at the mean response time, by about 30 seconds. With such direct evidence on the benefits provided by a technology, it is hard to pass up the opportunity to compare the benefits to the costs. Rapidly increasing investments in technology have been blamed for the increase in health care costs over the past several decades (see, e.g., Newhouse 1992). While 911 is just one technology and it is difficult to draw any general conclusions (in all probability, county-level governments face different incentives to invest in technology and encourage its use than, for instance, hospitals), it would be interesting to see what the implicit cost of the new technology is per life saved. Table 4.10 provides estimates of the effect a reduction in the time to scene has on the probability a patient dies (and the authors cite clinical studies that give similar measures), and table 4.7 documents the effect of 911 service level on the time to scene. With more information like that provided for

Berks County on the cost of 911 systems, one could estimate the implicit cost per life saved. (Such a calculation could almost be done based on the information provided in the paper currently. One important missing factor is the number of ambulance trips in Berks County.)

To complete the accounting of the impact of 911 investments on patient lives saved, one would need to account for the authors' results on technology adoption by hospitals. For instance, if elaborate and highly productive 911 systems cause hospitals to engage in technology races and overinvest in catheterization laboratories, the overall benefits would be reduced.

A second notable result in this paper is the concrete evidence it provides on the extent to which different patients are allocated to hospitals with different technology levels. For instance, the results in table 4.9 suggest that patients that are brought to hospitals with better facilities are more likely to have longer ambulance rides to the hospital, and table 4.12 suggests that patients have a better chance of getting to a hospital with higher technological capabilities if the local county has E911. Both results suggests that even with a life-threatening, time-sensitive disease, patients with different unconditional probabilities of survival are allocated to different hospitals. That result suggests that any attempts to compare outcomes across hospitals that do not control for patient selection issues should be viewed with caution. It also emphasizes the value of efforts to control for initial allocation of patients (e.g., McClellan and Newhouse 1997).

References

McClellan, M., and J. P. Newhouse. 1997. The Marginal Cost-Effectiveness of Medical Technology: A Panel Instrumental-Variables Approach. *Journal of Econometrics* 77 (March): 39–64.

Newhouse, J. P. 1992. Medical Care Costs: How Much Welfare Loss? *Journal of Economic Perspectives* 6 (summer): 3–21.

Comment on Chapters 3 and 4

Karen Norberg

In a way, the two papers in this section are both concerned with the adoption of new information technologies: Athey and Stern have studied the adoption of an enhanced 911 technology that changes the delivery of ambulance-based emergency care and transport, and McClellan and Staiger have introduced a new statistical method that may improve the comparison of quality among hospitals.

Karen Norberg is assistant professor of psychiatry at Boston University Medical School and a clinical associate of the National Bureau of Economic Research.

Athey and Stern

In out-of-hospital cardiac arrest, the time between collapse and initiation of CPR is an important determinant of the likelihood of survival (Berek et al. 1997). There is wide variation across the United States in the level of 911 emergency services provided within the community. The most recent advance, known as Enhanced 911, involves the automatic identification of the address from which a call is made, and a database of information about the location of all addresses in the community. Athey and Stern find that an ambulance arrives at the scene of a cardiac arrest about 5 percent faster, and the patient is transported from the scene to the hospital about 10 percent faster, in Pennsylvania counties with Enhanced 911 compared to other levels of service. Protocols for 911 services specify that sicker patients are taken to hospitals with higher levels of specialization, and higher levels of 911 technology resulted in more discrimination about which patient is taken to which hospital.

Why do some communities adopt Basic or Enhanced 911 technology while some do not? Presumably, the counties that have adopted enhanced 911 are those that could afford the investment, and whose public officials believed that the technology would significantly benefit the county. Although a community's demand for Enhanced 911 services may be driven by the desire for crime or fire protection as well as by a demand for emergency medical service, the most significant predictors of level of 911 adoption appear to be county population, per capita income, and general political orientation toward government services.

McClellan and Staiger

Different hospital markets may be characterized by different levels of emergency medical service infrastructure, different community standards of care, different degrees of competition, different demographics, and different prevalence of illness. Such community differences may confound efforts to study the effects of hospital quality in a national sample. McClellan and Staiger introduce the use of a "filtered" risk-adjusted mortality rate (RAMR) to compare the outcomes of patients admitted with acute myocardial infarction. This filtered RAMR yields a much higher signal-to-noise ratio than ordinary methods, and makes it possible to compare individual hospitals within the same market with much greater confidence in the meaningfulness of the comparisons that are made.

Like other investigators, McClellan and Staiger find that for-profit and government hospitals have higher mortality than not-for-profit in their national sample. Their three case studies suggest a more complicated picture. In case 1, the two for-profit hospitals had lower mortality than the others in the community. In case 2, there were improvements in the mortality rates of hospital 2 at the times of two different purchases by two different for-profit chains; and in case 3, the two hospitals that changed ownership also showed the greatest improvements in mortality, but these changes in ownership involved a transition from government and for-profit to not-for-profit status.

Cases 1 and 2 are consistent with the hypothesis that for-profit hospitals may be more likely to enter markets where lower quality management has created attractive takeover opportunities; although they may, on average, be functioning in markets with lower average quality, some for-profit hospitals could provide higher than average services within their markets. Case 3 reminds us that any change in hospital ownership could be associated with improvement in productivity in the short run; the fact of a change in ownership implies that both buyer and seller foresaw an opportunity for benefit in the exchange. There are a great many public concerns about for-profit hospitals that are not explored in the present study; in any case, we cannot draw systematic conclusions about for-profit hospital ownership and quality of care from just three examples, but the case studies are enough to point out the hazard of oversimplified conclusions from aggregate national data.

McClellan and Staiger's filtered RAMR results in a dramatic reduction in the "noise" associated with mortality as a quality-of-care outcome measure. However, their method is subject to all of the other problems with risk adjustment, and a few caveats about generalizability. It is easy to imagine a study such as this one becoming the basis for a public quality-of-care "report card" in a particular hospital market. Clinicians, in particular, are notoriously skeptical of such report cards (Angell and Kassirer 1996; Chassin 1996; Epstein 1998). There are two principal reasons for this skepticism.

First, risk adjustment is hard to do well. In many clinical conditions, the patient's illness and other characteristics are much stronger predictors of outcome than are any nuances of medical intervention; differences in the case mix between hospitals may overshadow the effects of any true differences in the quality of care. However, the only risk factors that can be entered into a regression are those that have been measured. Administrative and clinical records may be sketchy about known clinical risk factors, and of course, they cannot account for risk factors that are still unknown. Instrumental variables are an alternative way around this problem; process measures, rather than mortality, may also be less confounded by problems of patient selection (Brook, McGlynn, and Cleary 1996; Chen et al. 1999).

Second, based on a study such as this one, it may be tempting to make generalizations about quality of care in for-profit hospitals. However, institutional quality in one outcome may or may not be correlated with institutional quality in another outcome. A hospital's neonatal mortality rate may be unrelated to its mortality rate from acute myocardial infarctions; its cardiac surgery service may have a different reputation from its orthopedics. Hospitals may offer high-quality care as a "loss leader" in services (such as cardiac care) where there may be significant market competition, and may provide lower quality care in services for which there is less competition. As Athey and Stern point out, hospitals may compete based on the criteria used by the emergency services that provide patient referrals. Regulators, of course, hope that the use of public report cards will lead to higher quality of care in the services reported, but this may be accomplished by lowering the quality of care in services that are not publicly reported. The qualities surveyed will depend on feasibility and on the priorities of the agency collecting the information; the feasibility of collecting certain information depends on existing administrative infrastructures, which themselves reflect the past priorities of the public and private institutions involved. For better or for worse, single-focus report cards may increase the influence of the targeted services within the hospitals in the community, as the general reputation of each institution may depend on the performance of its most visible department.

Most hospital quality information is collected by single entities, such as hospitals, insurers, or health maintenance organizations. Such information is usually treated as highly confidential, and it is unclear how often such agencies are able to use the information in a way that actually leads to quality improvement. Higher quality studies, with more sensitive and stable measures, may improve the credibility of internally collected data and may increase the acceptability of public reporting among clinicians and provider institutions.

References

Angell, M., and J. P. Kassirer. 1996. Quality and the Medical Marketplace—Following Elephants. *New England Journal of Medicine* 335 (12): 883–85.

Berek, K., A. Schinner, C. Traweger, P. Lechlietner, M. Baubin, and F. Aichner. 1997. The Prognostic Significance of Coma-Rating, Duration of Anoxia, and Cardiopulmonary Resuscitation in Out-of-Hospital Cardiac Arrest. *Journal of Neurology* 244: 556–61.

Blumenthal, D. 1996. Part 1: Quality of Care: What Is It? *New England Journal of Medicine* 335 (12): 891–94.

Brook, R. H., E. A. McGlynn, and P. D. Cleary. 1996. Part 2: Measuring Quality of Care. *New England Journal of Medicine* 335 (13): 966–70.

Chassin, M. R. 1996. Part 3: Improving the Quality of Care. *New England Journal of Medicine* 335 (14): 1060–63.

Chen, J., M. J. Radford, Y. Wang, T. Marciniak, and H. M. Krumholz. 1999. Do "America's Best Hospitals" Perform Better for Acute Myocardial Infarction? *New England Journal of Medicine* 340 (4): 286–92.

Epstein, A. 1998. Rolling Down the Runway: The Challenges Ahead for Quality Report Cards. *Journal of the American Medical Association* 279 (21): 1691–96.

Kassirer, J. 1999. Hospitals, Heal Yourself. *New England Journal of Medicine* 340 (4): 309–10.

Schneider, E. C., and A. M. Epstein. 1998. Use of Public Performance Reports: A Survey of Patients Undergoing Cardiac Surgery. *Journal of the American Medical Association* 279 (20): 1638–42.