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THE ADOPTION AND IMPACT OF ADVANCED EMERGENCY RESPONSE SERVICES

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ABSTRACT

This paper studies the causes and consequences of the adoption of technology by hospitals and public emergency response systems, focusing on Basic and Enhanced 911 services. Basic 911 allows people within a given locality to access specialized call-takers and ambulance dispatchers using the single telephone number 911. Enhanced 911 is characterized by telecommunications equipment and information technology which identifies the location of emergency callers. We begin by exploring the distribution of 911 systems among counties in the U.S., showing that this locally provided service responds to income and political factors as well as population and density of a county. Then, using a database of cardiac patients in Pennsylvania in 1995, we are able to characterize some of the productivity efforts of 911 services. We show that Enhanced 911 reduces response times, which in turn reduce mortality. Further, we find that the pre-hospital system interacts with the allocation of patients to hospitals in several ways. First, patient severity affect the allocation of patients to high-technology hospitals. Second, conditional on the availability of advanced cardiac care facilities, counties with 911 systems allocate cardiac patients to hospitals with better technology. Finally, hospitals with more advanced emergency and cardiac technology treat a higher share of cardiac patients who make use of the pre- hospital system.

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I. 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 CPR and defibrillation is claimed to be an important determinant of the probability of survival.[1] As well, 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 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 which 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. 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 callers' 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 which 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 which 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 pre-hospital 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 which entail investments in information technology and telecommunications equipment.

As a service enbabled by investment in information technology, emergency response systems belong to the substantial portion of the economy which has defied accurate productivity measurment (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 which 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 takes 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 which 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 which 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 which are an important component of the quality of emergency medical services. The detailed nature of the dataset allows us to control for a variety of patient characteristics, as well as 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% 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 which change their level of 911 technology during our sample period. Moreover, patients are transported from the scene of an incident to the hospital approximately 10% 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%) and only a small portion of our sample resides in counties with no 911 technology (approximately 20%), 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 towards 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 which 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%). Instead, it seems to be the availability of medical technology in nearby hospitals which 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 pre-hospital 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 emrgency 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 II, 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 which arise in the analysis of these systems. Section III presents the data which we will use to conduct the analysis. Sections IV, V, and VI 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.

II. 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 pre-hospital 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 pre-hospital and in-hospital emergency care. Finally, we describe the factors which 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 1960's, emergencies were reported to a telephone operator (whose training and equipment usually did not accomodate the efficient handling of emergency) or by directly contacting a particular public service agency (requiring individuals to find the 7-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, 1988). Following a model developed in Europe after WWII (most particularly the 9-9-9 system in Great Britain), the first 911 systems were introduced into the US 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:

- 911 is dialed by an individual in an emergency
- 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, for example, 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 which 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.

911 systems have several advantages in reducing response times. 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 which 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 or adults for 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 pre-arrival 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 which 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 hospitals (see Figure 1 for a representative county protocol). In Figure 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 judgement, resolve a tradeoff 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 which 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 where 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 which 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 is very labor-intensive and usually takes at least six months to a year to complete. Furthermore, the telephone equipment, caller identification database, and the 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 a typical county has a startup cost of between $1 million and $4 million.

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 $2.3 million.[5] Its budget comes primarily from a tax on telephone lines ($.97 per line each month) as authorized by state legislation (Figure 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 which 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 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.

III. The Data

As mentioned earlier, little previous empirical research has been done on the pre-hospital 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 1 and 2 provide definitions, sources, and means and standard deviations for all variables.

County-Level Variables

For the purposes of this paper, we characterize the pre-hospital emergency infrastructure and its determinants at the county level. Unfortunately, we are not aware of a comprehensive accounting of 911 practices in the U.S.. 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 which 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 (BASIC 911) or enhanced 911 (ENHANCED 911) system. In the national sample, 75% 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 which 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 towards systems with higher levels of 911 service, especially under-counting counties with no county-wide 911 system; in Pennsylvania, where we have a comprehensive accounting of the counties, 30 of the 54 of the counties had E911 at the start of 1995 (see Figure 3).

In addition to the county level variables, we include in our analysis two "911" variables which are drawn from NENA state-level surveys which 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 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 county's political demand for public expenditures (Perot voters were noted for their strong beliefs in limited government).

Hospital-Level Variables

Our information about hospitals is obtained from the American Hospital Association (AHA) annual hospital inventory survey. We use this information 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 which required ambulance service in 1995 (COUNTY CARDIAC PATIENTS). Second, in our patient-level productivity analysis, we link hospital characteristics to our patient-level database in order to control for hospital quality as well as analyze the allocation process which 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 whether the hospital is an urgent care provider (URGENT) and the level of certified emergency care (TRAUMA CNTR LEVEL). In our analysis of individual data, we examine the case of cardiac care and so 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 overall features of each hospital including its size (EMERGENCY ROOM VOLUME; HOSPITAL DOCTORS) and the number of residents (HOSPITAL RESIDENTS).

Patient-Level Variables

Our patient-level variables are drawn from a database of every ambulance ride in Pennsylvania which could be linked to a hospital discharge during 1995 (approximately 170,000 observations). This dataset 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 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 datasets, 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 0-15 which 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 dataset, including their insurance status, age, and sex. As well, we observe some information about the types of procedures administered by the emergency response paramedics, including whether the patient receives defibrillation treatment prior to arrival at the hospital. However, since the decision to defibrillate a patient is conditioned on patient characteristics which 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 afterwards.

IV. The Determinants of the 911 System Adoption

We begin by describing the characteristics of three groups of counties in Pennsylvania: those with no 911, Basic 911, and Enhanced 911. Because 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 which exclude these four counties in our subsequent regression analysis). There are some systematic differences between the demographic characteristics of the counties which 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 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 state-wide 911 system, perhaps recognizing the economies of scale associated the provision of the service at the state level.

As described in Section II, 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 which determine the allocation of 911 services (and their productivity benefits) to different subsets of the population. Thus, in Table 4, 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. As well, 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 which oversee 911 centers. We interpret this result to indicate that states which 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 political and regulatory factors which may be unrelated to efficiency.

The latter two specifications in Table 4 include a variable whieh 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 which 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.

V. 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 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 which 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 dataset, 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 which provide direct evidence about the benefits of faster response times for mortality.

Building on our analysis from Section II, 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 tradeoff 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 tradeoff 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 which 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 5 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% of cardiac emergencies result in death. In contrast, even excluding the largest four counties, the average mortality rate in counties with E911 is 7% (see Figure 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_HOSPITAL, 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 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 report cardiac arrest in the Enhanced 911 group. Finally, many more patients report defibrillation (before reaching the hospital) in the No 911 counties. This might be due to differences in scoring or poor record-keeping 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 which receives the patients. None of the No 911 patients receive treatment in a certified trauma center, and only a quarter go 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 6). There are four specifications, which include a number of patient-level as well as county-level covariates (the results in Tables 6-8 about the effects of patient-level characteristics are generally robust to specifications which include county fixed effects instead of county-level covariates). The 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 which 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 dataset.

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 dataset which 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% slower than counties with E911, while counties with Basic are approximately 8% 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 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 who changed during the year. The county which changed from Basic to Enhanced 911 saw a 14% decrease in its TIME_TO_SCENE, while the counties which changed from No 911 to Basic saw a decrease which is not statistically significant. The weaker results about changes from No 911 to Basic 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 7 analyzes the determinants of TIME_AT_SCENE, following the same set of specifications as in Table 6. TIME_AT_SCENE is negatively related to both TIME_TO_SCENE and TIME_TO_HOSPITAL. 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 8 considers the determinants of TIME_TO_HOSP. Again, the specifications parallel Tables 6 and 7. 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 the number of hospitals per mile (which decreases TIME_TO_HOSP sharply), as well as 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 which 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 (Figure 4 and Table 9). We begin with a simple reduced-form regression of mortality on 911 as well as the controls from Tables 6-8. 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 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 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 which 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 which 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 non-urgent symptons 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 non-emergency patients to better hospitals.

VI. The Role of Emergency Response Systems in Allocating Patients to Hospitals

As described in Sections I and II, the pre-hospital 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 availability of a hospital with advanced technologies in her county. Table 10 shows that 80% of patients in our dataset 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% 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 dataset. Table 10 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 11, we explore further the factors which 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 which 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 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 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 11 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 which 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 deter particular types of patients (the uninsured or patients whom 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 12 presents a results which relate the proportion of a county's patients in the dataset 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 which seem to impact 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 pre-hospital system and technology adoption should be considered in analyses of the incentives for investment by hospitals.

One important caveat to our interpretation of Table 12 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 some hospitals characterized by higher than average quality, larger number 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 who 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 pre-hospital emergency response system available in a given county. However, in our preliminary analysis of this dataset, we have not found a robust interaction effect.

VII. Conclusions

From our analysis in this paper, we draw several conclusions which we hope will impact 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 which arises in studies which take allocation as exogenous or which do not account for the heterogeneity in county mortality rates which are induced by higher levels of pre-hospital care (such as lower response times or on-the-scene defibrillation). Further, the incentives generated by the pre-hospital 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 pre-hospital 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 pre-hospital infrastructure and hospital competition. For example, we find that patients are allocated by the pre-hospital system according to their severity and the technology which a hospital employs (see Tables 11 and 12); it is left to future work to evaluate whether these allocative effects are reflected in terms of strategic investment behavior by hostpials.

Examining 911 services also provides a glimpse into the challenges (and types of data) which 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 idiosyncratic characteristics (in this case, different patients experience different diagnoses and different degrees of severity of illness). By developing and analyzing a novel dataset, 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 towards 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., Pepe, P.E., and Clark, P.S., 1993, "Survival in the elderly after out-of-hospital cardiac arrest," *Critical Care Medicine* 21(11): 1645-1651.

Bresnahan, Timothy F.; Gordon, Robert J., eds., 1997, *The Economics of New Goods.* National Bureau of Economic Research (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): 646-650.

Cummins, R.O., Ornato, J.P., Thies, W.H., and Pepe, P.E., 1991. The American Heart Association Subcommittee on Advanced Cardiac Life Support. "Improving survival from sudden cardiac arrest: the `chain of survival' approach," *Circulation* 83 (5): 1832-1847.

Fischer, M., Fischer N.J., and Schuttler, J., 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," *JACEP* 6(9): 389-392.

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., Pomrehn, P.R., and Brown, D.D., 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): 200-6.

Larsen, M.P., Eisenberg, M.S., Cummins R.O., and Hallstrom, A.P., 1993, "Predicting survival from out-of-hospital cardiac arrest: a graphic model," *Annals of Emergency Medicine* 22(11): 1652-8.

Lewis, R., et al, 1982, "Reduction of mortality from prehospital myocardial infarction by prudcnt patient activation of mobile coronary care system," *American Heart Journal* 103(1): 123-129.

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, OH: National Emergency Number Association.

Siler, Kenneth P., 1975, "Predicting Demand for Publicly Dispatched Ambluances in a Metropolitan Area," *Health Services Research* 10(3): 254-63.

Smith, Ken, 1988, "The ambulance service: past present, and future," *The Practitioner* 232: 879-82.

Tresch, D.D., Thakur, R., Hoffman, R., 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," mimeo, Carnegie Mellon University.

Weston C.F., Wilson, R.J., and Jones, S.D., 1997, "Predicting survival from out-of-hospital cardiac arrest: a multivariate analysis," *Resuscitation* 34(1): 27-34.

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, Eisenberg, Cummins, and Hallstrom (1993), Tresch, Thakur, and Hoffman (1989), and Weston, Wilson, and Jones (1997).

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.

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 9-1-1 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 which 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.

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/.

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 county-wide. This selection process under-represents counties for which there is no county-wide 911 system.

TABLE 1
VARIABLES* & 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 CHAR.		
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 = 1if Insurance Status = Medicare	PA EMS
MEDICAID	Dummy = 1if Insurance Status = Medicaid	PA EMS
PRIVATE	Dummy = 1if Insurance Status = Private or Govt.	PA EMS
SELF PAY	Dummy = 1if Insurance Status = Self-Pay	PA EMS
OTHER	Dummy = 1if Insurance Status = Other	PA EMS
HOSPITAL CHARACTERISTICS		
URGENT CARE CENTER	Dummy =1 if Certified Urgent Care Center	AHA
CATH LAB	Dummy = 1 if CardiacCatheterization 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 Certifed County Trauma Hospital	AHA
EMERGENCY ROOM VOLUME	Total # of Emergency Room Visits in 1995 in Thousands	AHA
HOSPITAL DOCTORS	# of FTE MDs on Staff in Hospital	AHA
HOSPITAL RESIDENTS	# of Medical Residents on Staff in Hospital	AHA

	DEFINITION	SOURCE
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	# of HOSPITALS IN COUNTY / # OF SQ MILES	AHA / CCDB
COUNTY CARDIAC PATIENTS	# of Recorded Cardiac Incidents in 1995	PA EMS
COUNTY DEMOGRAPHICS (Reference Year = 1992)		
POPULATION	County Population / 1000	CCDB
DENSITY	POPULATION / County Square Miles	CCDB
INCOME PER CAP	County-Level Income per Capita / 1000	CCDB
CRIMERATE	Crime Rate (Incidents per 100K Population)	CCDB
VCRIMERATE	Violent Crime Rate (Incidents per 100 K 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

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

TABLE 2A
SUMMARY STATISTICS
(COUNTY-LEVEL AVERAGES)

	PA SAMPLE		NATIONAL SAMPLE	
	MEAN	STANDARD DEVIATION	MEAN	STANDARD DEVIATION
# OF COUNTY / SYSTEMS	58.000*		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	1264.8800	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 (CRIMERATE 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

* Out of 54 PA counties for which we observe the 911 Level, 4 experienced mid-year changes, yielding 58 "County System" observations.

TABLE 2B
PATIENT-LEVEL SUMMARY STATISTICS
(PA SAMPLE ONLY)

	MEAN	STANDARD DEVIATION
# OF COUNTIES	54.0000	
# OF PATIENT OBS	24664.0000	
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 CHAR.		
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

TABLE 3
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)
# OF COUNTIES	11.0000	16.0000	31.0000	27.0000
# OF CARDIAC OBS	2039.0000	3445.0000	19180.0000	10993.0000
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

TABLE 4
911 DEMAND REGRESSIONS
(NATIONAL SAMPLE)

	DEPENDENT VARIABLE = 911_LEVEL			
	BASE REGRESSION (OLS)	BASE REGRESSION (ORDERED LOGIT)	INCLUDE COUNTY HOSPITAL INFRASTRUCTURE	INCLUDE HOSP INF (ORDERED LOGIT)
COUNTY HOSPITAL INFRASTRUCTURE				
CERT. TRAUMA CNTR.			-0.06458 (0.06221)	-0.44596 (0.29835)
COUNTY DEMOGRAPHIC CHARACTERISTICS				
L POPULATION	0.11172 (0.02972)	0.37180 (0.13783)	0.11555 (0.02995)	0.37754 (0.13877)
DENSITY	0.000004 (0.000037)	0.00078 (0.00069)	0.000008 (0.000037)	0.00088 (0.00070)
INCOME PER CAP	0.01207 (0.00956)	0.06675 (0.05483)	0.01266 (0.00958)	0.06894 (0.05516)
CRIMERATE	0.27501 (1.14780)	4.34417 (5.69929)	0.33910 (1.14940)	4.77066 (5.74605)
POLICE EXP	-0.00108 (0.00081)	-0.01212 (0.00747)	-0.00104 (0.00081)	-0.01176 (0.00781)
HEALTH EXP	0.00088 (0.00243)	0.04322 (0.03065)	0.00113 (0.00244)	0.04601 (0.03077)
COUNTY POLITICAL CHARACTERISTICS				
% REPUBLICAN	-0.00332 (0.00284)	-0.01023 (0.01282)	-0.00344 (0.00285)	-0.01050 (0.01286)
% PEROT	-0.00854 (0.00402)	-0.04217 (0.01774)	-0.00873 (0.00386)	-0.04301 (0.01781)
STATE LEGISLATION				
911_TRAIN_LAW	0.16148 (0.05926)	0.47014 (0.23082)	0.15724 (0.05940)	0.46095 (0.23085)
911_TRAIN_PLAN	0.26570 (0.06372)	1.04053 (0.27448)	0.26365 (0.06375)	1.04598 (0.27465)
CONSTANT	0.41650 (0.31374)		0.38349 (0.31533)	
ORD. LOGIT PARAMETERS		Insignificant		Insignificant
OBSERVATIONS	722	722	722	722
LOG-LIKELIHOOD		-444.51963		-443.44308
R-SQUARED	0.1192		0.1206	

TABLE 5
DISTRIBUTION OF PENNSYLVANIA 911 LEVEL
(PATIENT-LEVEL AVERAGES)

	COUNTY 911 LEVEL			
	No 911	Basic 911	Enhanced 911	Enhanced 911 (Excluding 4 largest counties)
# OF COUNTIES	11.0000	16.0000	31.0000	27.0000
# OF CARDIAC OBS	2039.0000	3445.0000	19180.0000	10993.0000
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 CHAR.				
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)				
GLASGOW0	0.0711	0.0761	0.0357	0.0259
GLASGOW3	0.0436	0.0369	0.0455	0.0432
GLASGOW4-9	0.0118	0.0134	0.0153	0.0121
GLASGOW10-12	0.0098	0.0171	0.0171	0.0140
GLASGOW13-14	0.0392	0.0360	0.0414	0.0388
GLASGOW15	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	1467.8430	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 RESDIENTS	5.3198	12.0136	32.3299	17.4391
EMGCY ROOM VOLUME	30.4250	27.0173	30.3736	31.0908

TABLE 6
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 (0.00654)	-0.15461 (0.00763)	-0.19951 (0.02159)
L TIME_TO_HOSP		0.32575 (0.00507)	0.3462 (0.00607)	0.36371 (0.02057)
911 LEVEL				
NO 911	0.09383 (0.01698)	0.01831 (0.01557)	0.05215 (0.01656)	0.08953 (0.07063)
BASIC 911	0.07538 (0.01341)	0.0222 (0.01228)	0.00226 (0.01261)	0.13546 (0.04305)
PATIENT CHARACTERISTICS				
MALE	0.03631 (0.0083)	0.01558 (0.00759)	0.01846 (0.00924)	0.04848 (0.02857)
AGE	0.00745 (0.00205)	0.00398 (0.00188)	0.00197 (0.00252)	0.01683 (0.0076)
AGE_SQUARED	-0.00006 (0.00002)	-0.00002 (0.00001)	-0.00001 (0.00002)	-0.00011 (0.00006)
CARDIAC ARREST	-0.12503 (0.01787)	-0.06098 (0.01635)	0.05545 (0.03558)	0.15153 (0.11695)
DEFIBRILLATE	0.03474 (0.00846)	0.02764 (0.00773)	0.02735 (0.0095)	0.02532 (0.03216)
GLASGOW TRAUMA SCORE (15=Least Severe; 3=Most Severe; 0=Unknown)				
GLASGOW 0	1.60486 (0.20163)	1.33791 (0.18496)	0.41029 (0.22467)	-0.05927 (0.18582)
GLASGOW 3	1.63347 (0.20315)	1.41933 (0.18649)	0.41626 (0.22637)	-0.10982 (0.18081)
GLASGOW 4-9	1.6558 (0.20322)	1.4468 (0.18644)	0.47398 (0.22688)	
GLASGOW 10-12	1.70663 (0.20283)	1.43213 (0.18607)	0.49918 (0.22608)	-0.17747 (0.18852)
GLASGOW 13-14	1.6681 (0.20118)	1.39132 (0.18456)	0.45937 (0.22433)	0.0092 (0.15863)
GLASGOW 15	1.6887 (0.20057)	1.38023 (0.18403)	0.47959 (0.22347)	-0.08971 (0.1426)

INSURANCE STATUS (EXCLUDED CATEGORY = MEDICARE)				
MEDICAID	-0.08647 (0.02068)	-0.0497 (0.0189)	-0.02478 (0.02335)	0.1198 (0.06903)
PRIVATE	-0.00113 (0.01306)	-0.01811 (0.01193)	-0.02074 (0.01476)	-0.02352 (0.04388)
SELF_PAY	-0.00863 (0.03815)	-0.0371 (0.03484)	-0.0866 (0.03826)	-0.27909 (0.20312)
OTHER	-0.01691 (0.02288)	-0.0206 (0.0209)	-0.01409 (0.02733)	0.10725 (0.06999)
COUNTY HOSPITAL INFRASTRUCTURE				
CERT. TRAUM CNTR	0.15789 (0.01474)	0.09753 (0.01349)	0.13947 (0.0196)	
L HOSP PER SQ. MILE	-0.12588 (0.01189)	-0.04815 (0.01092)	-0.00084 (0.01412)	
L COUNTY CARDIAC PATIENTS	-0.0567 (0.01177)	-0.08468 (0.01077)	-0.10222 (0.01176)	
COUNTY DEMOGRAPHICS				
L POPULATION	-0.09277 (0.03064)	-0.03693 (0.02812)	0.0374 (0.02924)	
DENSITY	0.0315 (0.0055)	0.02544 (0.00505)	-0.33748 (0.04916)	
L INCOME PER CAP	0.10874 (0.03698)	0.22698 (0.03388)	0.72577 (0.04689)	
VCRIMERATE	6.98859 (4.24895)	9.77737 (3.88727)	-6.69225 (4.69215)	
L POLICE EXP	0.06323 (0.0224)	0.03356 (0.02049)	-0.03753 (0.0219)	
L HEALTH EXP	-0.013 (0.00422)	-0.02067 (0.00386)	-0.01945 (0.00403)	
HOSPITAL CHARACTERISTICS				
URGENT CARE CENTER	-0.03722 (0.01138)	-0.04101 (0.0104)	-0.03001 (0.01389)	
CATH LAB	-0.03328 (0.01185)	-0.04442 (0.01084)	-0.04749 (0.01375)	0.20105 (0.04967)
OPENHEART FAC	0.02769 (0.01243)	0.0203 (0.01137)	0.02798 (0.01865)	
TRAUMA CNTR LEVEL	-0.06379 (0.01181)	-0.04453 (0.01079)	-0.04719 (0.01872)	
EMERGENCY ROOM VOLUME	-0.00031 (0.00025)	0.00046 (0.00039)	-0.00073 (0.00054)	0.00614 (0.05292)
HOSPITAL DOCTORS	0.00023 (0.00007)	-0.00075 (0.00023)	-0.00039 (0.00052)	-0.01573 (0.04498)
HOSPITAL RESIDENTS	0.00043 (0.00043)	0.00003 (0.00007)	0.00102 (0.00036)	
CONSTANT				1.241 (0.31835)
OBSERVATIONS	24664.0000	24664.0000	16477.0000	1635.0000
R-SQUARED	0.7040	0.7170	0.7170	0.2774

TABLE 7
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 (0.00611)	-0.1574 (0.00777)	-0.25261 (0.02734)
L TIME_TO_HOSP		-0.04943 (0.00529)	-0.05542 (0.00669)	-0.10568 (0.02515)
911 LEVEL				
NO 911	-0.18644 (0.01522)	-0.16716 (0.01501)	-0.18038 (0.01665)	-0.0343 (0.07951)
BASIC 911	-0.09558 (0.01202)	-0.08014 (0.01186)	-0.07043 (0.01271)	0.11722 (0.0485)
PATIENT CHARACTERISTICS				
MALE	-0.03912 (0.00744)	-0.03228 (0.00733)	-0.03712 (0.00932)	-0.03224 (0.03216)
AGE	0.00536 (0.00184)	0.00691 (0.00181)	0.00397 (0.00254)	0.00001 (0.00857)
AGE_SQUARED	-0.00001 (0.00001)	-0.00003 (0.00001)	-0.00001 (0.00002)	0.00002 (0.00007)
CARDIAC ARREST	0.02266 (0.01602)	-0.00199 (0.01581)	0.06571 (0.0359)	0.13014 (0.13162)
DEFIBRILLATE	0.03347 (0.00758)	0.03949 (0.00747)	0.0247 (0.00959)	0.06299 (0.03616)
GLASGOW TRAUMA SCORE (15=Least Severe; 3=Most Severe; 0=Unknown)				
GLASGOW 0	2.17322 (0.1807)	2.45456 (0.1783)	2.54128 (0.22585)	
GLASGOW 3	2.45973 (0.18206)	2.74229 (0.17964)	2.75759 (0.22742)	0.17614 (0.19364)
GLASGOW 4-9	2.30703 (0.18212)	2.58851 (0.1797)	2.60049 (0.22805)	-0.26967 (0.20899)
GLASGOW 10-12	2.20594 (0.18177)	2.5016 (0.17938)	2.55148 (0.22728)	-0.03566 (0.19633)
GLASGOW 13-14	2.19037 (0.18029)	2.48132 (0.17792)	2.54956 (0.2255)	-0.15936 (0.1574)
GLASGOW 15	2.17405 (0.17975)	2.47202 (0.17741)	2.51962 (0.22466)	-0.10864 (0.13614)

INSURANCE STATUS (EXCLUDED CATEGORY = MEDICARE)				
MEDICAID	0.00908 (0.01854)	-0.00695 (0.01827)	0.00054 (0.02357)	-0.00165 (0.07775)
PRIVATE	-0.02494 (0.01171)	-0.023 (0.01153)	-0.0457 (0.01489)	-0.10748 (0.04931)
SELF PAY	-0.00607 (0.03419)	-0.00293 (0.03368)	-0.01054 (0.03861)	-0.51433 (0.22833)
OTHER	0.01131 (0.02051)	0.01001 (0.0202)	-0.00877 (0.02758)	-0.10236 (0.07877)
COUNTY HOSPITAL INFRASTRUCTURE				
CERT. TRAUM CENTER	-0.08111 (0.01321)	-0.05414 (0.01305)	-0.11849 (0.01979)	
L HOSP PER SQ. MILE	0.12706 (0.01066)	0.10232 (0.01054)	0.08358 (0.01423)	
L COUNTY CARDIAC PATIENTS	-0.10168 (0.01055)	-0.10644 (0.0104)	-0.104 (0.01187)	
COUNTY DEMOGRAPHICS				
L POPULATION	0.43383 (0.02746)	0.42261 (0.02706)	0.37463 (0.02935)	
DENSITY	-0.07099 (0.00493)	-0.06761 (0.00486)	-0.03212 (0.04967)	
L INCOME PER CAP	-0.19859 (0.03314)	-0.20712 (0.03275)	-0.11367 (0.04764)	
VCRIMERATE	35.18246 (3.80783)	36.32172 (3.75116)	52.4423 (4.71698)	
L POLICE EXP	-0.17784 (0.02007)	-0.16911 (0.01978)	-0.18477 (0.02205)	
L HEALTH EXP	-0.01733 (0.00378)	-0.01811 (0.00373)	-0.01583 (0.00406)	
HOSPITAL CHARACTERISTICS				
URGENT CARE CENTER	-0.03078 (0.0102)	-0.0354 (0.01005)	-0.07251 (0.014)	
CATH LAB	0.0825 (0.01062)	0.08175 (0.01047)	0.09871 (0.01386)	0.13936 (0.05607)
OPENHEART FAC	-0.07375 (0.01114)	-0.0707 (0.01098)	-0.11318 (0.0188)	
TRAUMA CENTER LEVEL	0.0035 (0.01059)	-0.0072 (0.01044)	-0.00458 (0.01889)	
EMERGENCY ROOM VOLUME	0.0008 (0.00038)	0.00087 (0.00038)	0.00174 (0.00054)	0.13112 (0.05946)
HOSPITAL DOCTORS	-0.00019 (0.00023)	-0.00017 (0.00022)	-0.00113 (0.00052)	-0.12205 (0.05052)
HOSPITAL RESIDENTS	0.00027 (0.00006)	0.00033 (0.00006)	0.00167 (0.00037)	-0.02503 (0.00954)
CONSTANT				3.20254 (0.33705)
OBSERVATIONS	24664.0000	24664.0000	16477.0000	1635.0000
R-SQUARED	0.7040	0.7170	0.7170	

TABLE 8
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 (0.00686)	0.47724 (0.00837)	0.44745 (0.0253)
L TIME_AT_SCENE		-0.07159 (0.00765)	-0.07504 (0.00906)	-0.10268 (0.02444)
911 LEVEL				
NO 911	0.15649 (0.01963)	0.10178 (0.0181)	0.10605 (0.01943)	0.09964 (0.07834)
BASIC 911	0.12466 (0.01551)	0.08459 (0.01427)	0.08718 (0.01479)	0.07311 (0.04786)
PATIENT CHARACTERISTICS				
MALE	0.04784 (0.00959)	0.02903 (0.00882)	0.02066 (0.01085)	0.03623 (0.0317)
AGE	0.01282 (0.00237)	0.00992 (0.00218)	0.00874 (0.00295)	0.00106 (0.00845)
AGE_SQUARED	-0.00011 (0.00002)	-0.00009 (0.00002)	-0.00008 (0.00002)	-0.00002 (0.00006)
CARDIAC ARREST	-0.18747 (0.02066)	-0.13073 (0.019)	-0.13198 (0.04177)	-0.00151 (0.03567)
DEFIBRILLATE	0.03532 (0.00978)	0.0224 (0.009)	0.03799 (0.01115)	-0.21201 (0.07646)
GLASGOW TRAUMA SCORE (15=Least Severe; 3=Most Severe; 0=Unknown)				
GLASGOW 0	1.6977 (0.23308)	1.14576 (0.21527)	1.15614 (0.26366)	-0.34525 (0.19073)
GLASGOW 3	1.65137 (0.23483)	1.10733 (0.21709)	1.11887 (0.26567)	-0.41187 (0.20586)
GLASGOW 4-9	1.57387 (0.23491)	1.00906 (0.21707)	1.07255 (0.26628)	-0.0466 (0.19352)
GLASGOW 10-12	1.73412 (0.23446)	1.13965 (0.2166)	1.14773 (0.26532)	-0.30685 (0.15502)
GLASGOW 13-14	1.73479 (0.23255)	1.1562 (0.21483)	1.16163 (0.26326)	-0.04845 (0.13422)
GLASGOW 15	1.8255 (0.23185)	1.23666 (0.21419)	1.2426 (0.26224)	-0.10085 (0.12976)

INSURANCE STATUS (EXCLUDED CATEGORY = MEDICARE)				
MEDICAID	-0.1092 (0.02391)	-0.07043 (0.02198)	-0.07683 (0.02741)	-0.07046 (0.04865)
PRIVATE	0.04206 (0.0151)	0.04077 (0.01388)	0.04224 (0.01732)	0.27275 (0.22532)
SELF PAY	0.08497 (0.04409)	0.08834 (0.04053)	0.11029 (0.04492)	-0.08129 (0.07766)
OTHER	0.01589 (0.02645)	0.02416 (0.02431)	-0.00221 (0.03209)	
COUNTY HOSPITAL INFRASTRUCTURE				
CERT. TRAUM CENTER	0.15252 (0.01704)	0.07711 (0.0157)	0.05555 (0.02305)	
L HOSP PER SQ. MILE	-0.18727 (0.01374)	-0.12268 (0.01269)	-0.09829 (0.01656)	
L COUNTY CARDIAC PATIENTS	0.0448 (0.01361)	0.06252 (0.01254)	0.09978 (0.01382)	
COUNTY DEMOGRAPHICS				
L POPULATION	0.00389 (0.03542)	0.07585 (0.03272)	0.06252 (0.03432)	
DENSITY	-0.01008 (0.00636)	-0.02905 (0.00587)	0.18259 (0.05779)	
L INCOME PER CAP	-0.44325 (0.04275)	-0.5054 (0.03932)	-0.46603 (0.05533)	
VCRIMERATE	5.65587 (4.91153)	5.09363 (4.52272)	2.34351 (5.50937)	
L POLICE EXP	0.01922 (0.02589)	-0.02139 (0.02383)	-0.08667 (0.0257)	
L HEALTH EXP	0.01653 (0.00488)	0.02102 (0.00449)	0.02104 (0.00473)	
HOSPITAL CHARACTERISTICS				
URGENT CARE CENTER	-0.00081 (0.01316)	0.0134 (0.0121)	0.00072 (0.01631)	0.16509 (0.05522)
CATH LAB	0.06756 (0.0137)	0.08813 (0.01261)	0.10653 (0.01613)	
OPENHEART FAC	-0.00712 (0.01437)	-0.02461 (0.01322)	-0.01003 (0.0219)	
TRAUMA CENTER LEVEL	-0.05772 (0.01366)	-0.02935 (0.01256)	-0.05217 (0.02198)	-0.02545 (0.0587)
EMERGENCY ROOM VOLUME	0.00025 (0.00049)	0.00012 (0.00045)	-0.00144 (0.00063)	0.02418 (0.04989)
HOSPITAL DOCTORS	0.00126 (0.00029)	0.00138 (0.00027)	0.00244 (0.00061)	0.01174 (0.00942)
HOSPITALRESIDENTS	0.00073 (0.00008)	0.00065 (0.00008)	0.00135 (0.00043)	1.67951 (0.33885)
CONSTANT				3.20254 (0.33705)
OBSERVATIONS	24664.000	24664.000	16477.000	1635.000
R-SQUARED	0.704	0.717	0.717	

TABLE 9
MORTALITY EQUATION

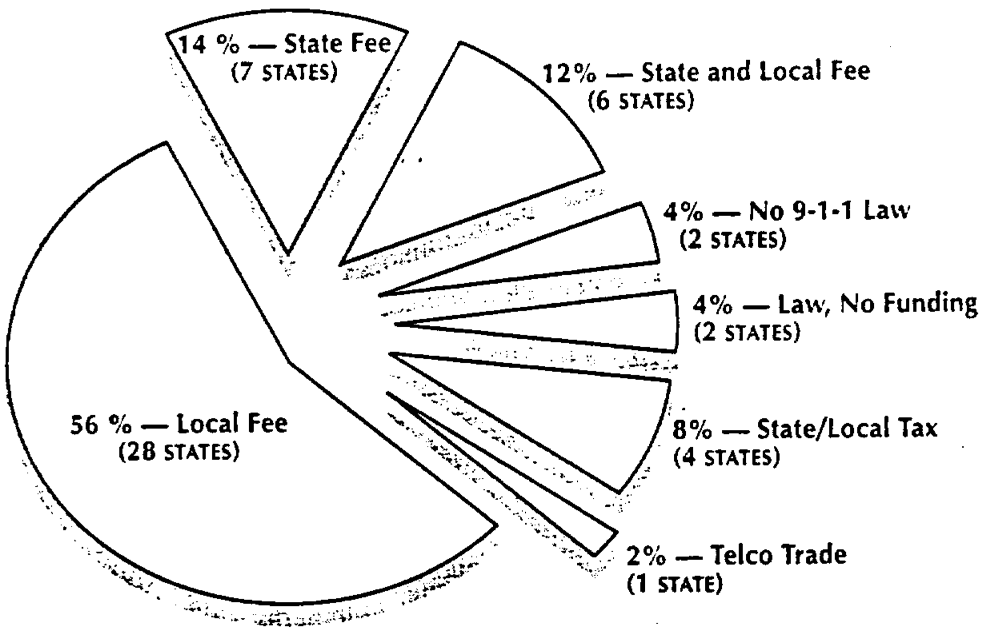
	DEPENDENT VARIABLE = DEATH OUTCOME DUMMY		
	REDUCED FORM (OLS)	BASE REGRESSION (OLS)	BASE REGRESSION (IV)*
TIME OUTCOMES			
L TIME_TO_SCENE		0.00535 (0.00268)	0.03122 (0.01974)
L TIME_AT_SCENE		0.01266 (0.00275)	0.04073 (0.01434)
L TIME_TO_HOSP		-0.00690 (0.00228)	0.01896 (0.01187)
911 LEVEL			
NO 911	-0.00104 (0.00658)		
BASIC 911	0.00030 (0.00520)		
PATIENT CHARACTERISTICS			
MALE	0.00529 (0.00322)	0.00591 (0.00322)	0.00479 (0.00329)
AGE	-0.00281 (0.00080)	-0.00276 (0.00080)	-0.00352 (0.00083)
AGE_SQUARED	0.00003 (6.06 e-6)	0.00003 (6.05 e-6)	0.00004 (6.26 e-6)
CARDIAC ARREST	0.01709 (0.00693)	0.01271 (0.00627)	0.02566 (0.00718)
DEFIBRILLATE	0.02500 (0.00328)	0.02441 (0.00326)	0.02149 (0.00342)
GLASGOW TRAUMA SCORE (15=Least Severe; 3=Most Severe; 0=Unknown & Default)			
GLASGOW 3	0.31672 (0.01177)	0.31605 (0.01146)	0.30487 (0.01249)
GLASGOW 4-9	0.19542 (0.01485)	0.19380 (0.01419)	0.19219 (0.01536)
GLASGOW 10-12	0.11793 (0.01423)	0.11838 (0.01419)	0.11426 (0.01449)
GLASGOW 13-14	0.02183 (0.01077)	0.02261 (0.01071)	0.01969 (0.01090)
GLASGOW 15	-0.01625 (0.00769)	-0.01459 (0.00762)	-0.02021 (0.00783)

TABLE 12
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)
HOSPITALRESIDENTS	0.0008 (0.0102)
INTENSITY OF RIVAL HOSPITAL COMPETITION	
# 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 HOSPITALRESIDENTS	0.0084 (0.0138)
CONSTANT	-0.1513 (0.7788)
OBSERVATIONS	101.0000
R-SQUARED	0.5419

FIGURE 1

How is 9-1-1 funded in the 50 states?



Minnesota Department of Administration — January 1995

FIGURE 2

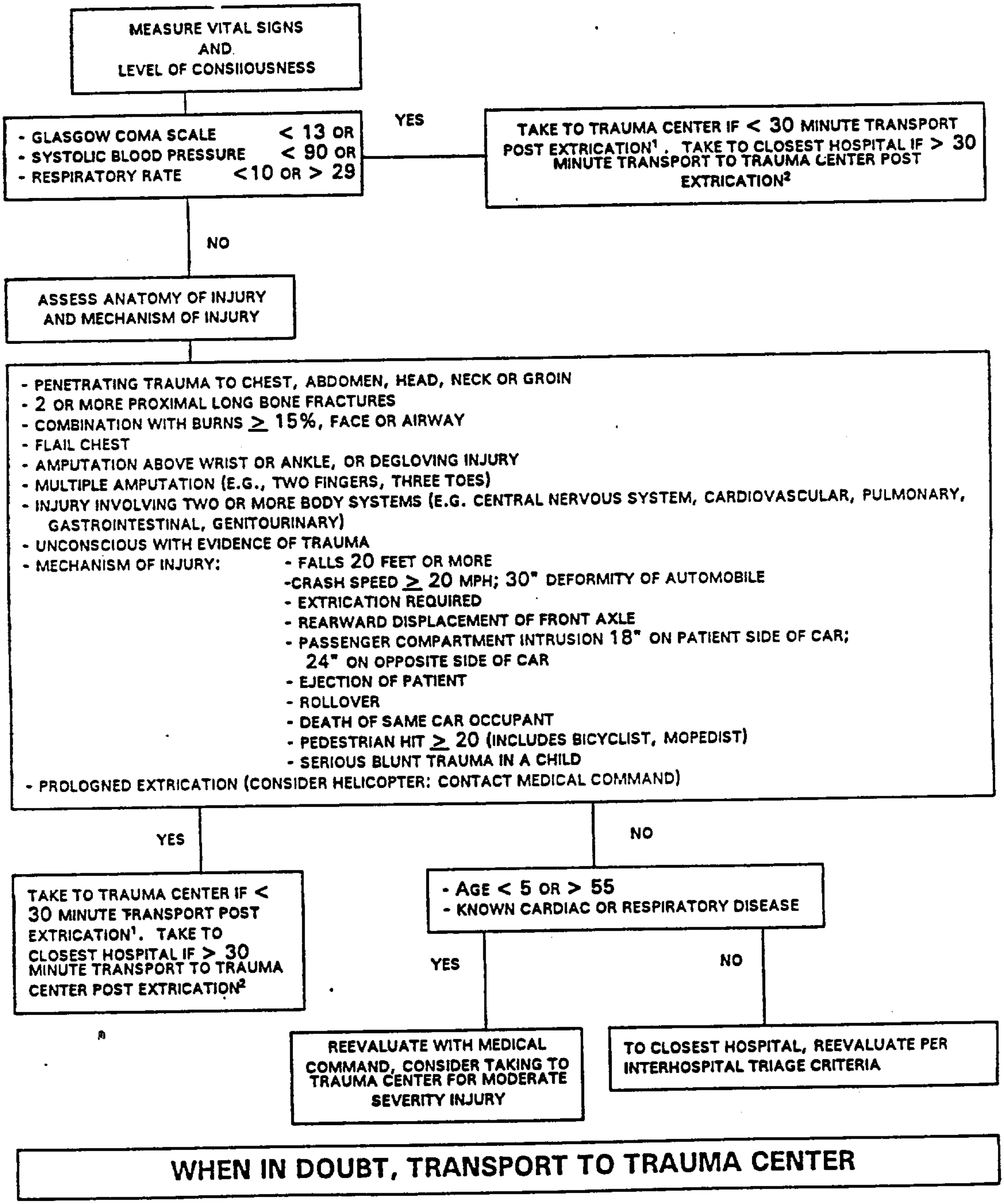
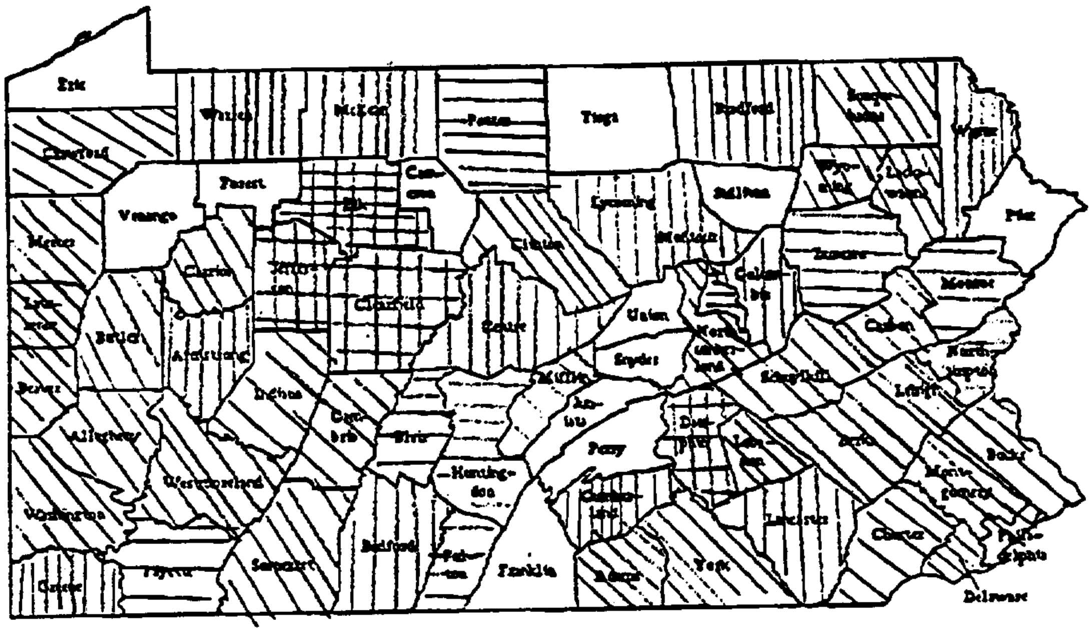

MEASURE VITAL SIGNS AND LEVEL OF CONSIIOUSNESS
- GLASGOW COMA SCALE < 13 OR
- SYSTOLIC BLOOD PRESSURE < 90 OR
- RESPIRATORY RATE <10 OR > 29
YES
TAKE TO TRAUMA CENTER IF < 30 MINUTE TRANSPORT POST EXTRICATION[1]. TAKE TO CLOSEST HOSPITAL IF > 30 MINUTE TRANSPORT TO TRAUMA CENTER POST EXTRICATION[2]
NO
ASSESS ANATOMY OF INJURY AND MECHANISM OF INJURY
- PENETRATING TRAUMA TO CHEST, ABDOMEN, HEAD, NECK OR GROIN
- 2 OR MORE PROXIMAL LONG BONE FRACTURES
- COMBINATION WITH BURNS ≥ 15%, FACE OR AIRWAY
- FLAIL CHEST
- AMPUTATION ABOVE WRIST OR ANKLE, OR DEGLOVING INJURY
- MULTIPLE AMPUTATION (E.G., TWO FINGERS, THREE TOES)
- INJURY INVOLVING TWO OR MORE BODY SYSTEMS (E.G. CENTRAL NERVOUS SYSTEM, CARDIOVASCULAR, PULMONARY, GASTROINTESTINAL, GENITOURINARY)
- UNCONSCIOUS WITH EVIDENCE OF TRAUMA
- MECHANISM OF INJURY:
- FALLS 20 FEET OR MORE
-CRASH SPEED ≥ 20 MPH; 30" DEFORMITY OF AUTOMOBILE
- EXTRICATION REQUIRED
- REARWARD DISPLACEMENT OF FRONT AXLE
- PASSENGER COMPARTMENT INTRUSION 18" ON PATIENT SIDE OF CAR; 24" ON OPPOSITE SIDE OF CAR
- EJECTION OF PATIENT
- ROLLOVER
- DEATH OF SAME CAR OCCUPANT
- PEDESTRIAN HIT ≥ 20 (INCLUDES BICYCLIST, MOPEDIST)
- SERIOUS BLUNT TRAUMA IN A CHILD
- PROLONGED EXTRICATION (CONSIDER HELICOPTER: CONTACT MEDICAL COMMAND)
YES
NO
TAKE TO TRAUMA CENTER IF < 30 MINUTE TRANSPORT POST EXTRICATION[1]. TAKE TO CLOSEST HOSPITAL IF > 30 MINUTE TRANSPORT TO TRAUMA CENTER POST EXTRICATION[2]
- AGE < 5 OR > 55
- KNOWN CARDIAC OR RESPIRATORY DISEASE
YES
NO
REEVALUATE WITH MEDICAL COMMAND, CONSIDER TAKING TO TRAUMA CENTER FOR MODERATE SEVERITY INJURY
TO CLOSEST HOSPITAL, REEVALUATE PER INTERHOSPITAL TRIAGE CRITERIA
WHEN IN DOUBT, TRANSPORT TO TRAUMA CENTER

FIGURE 3



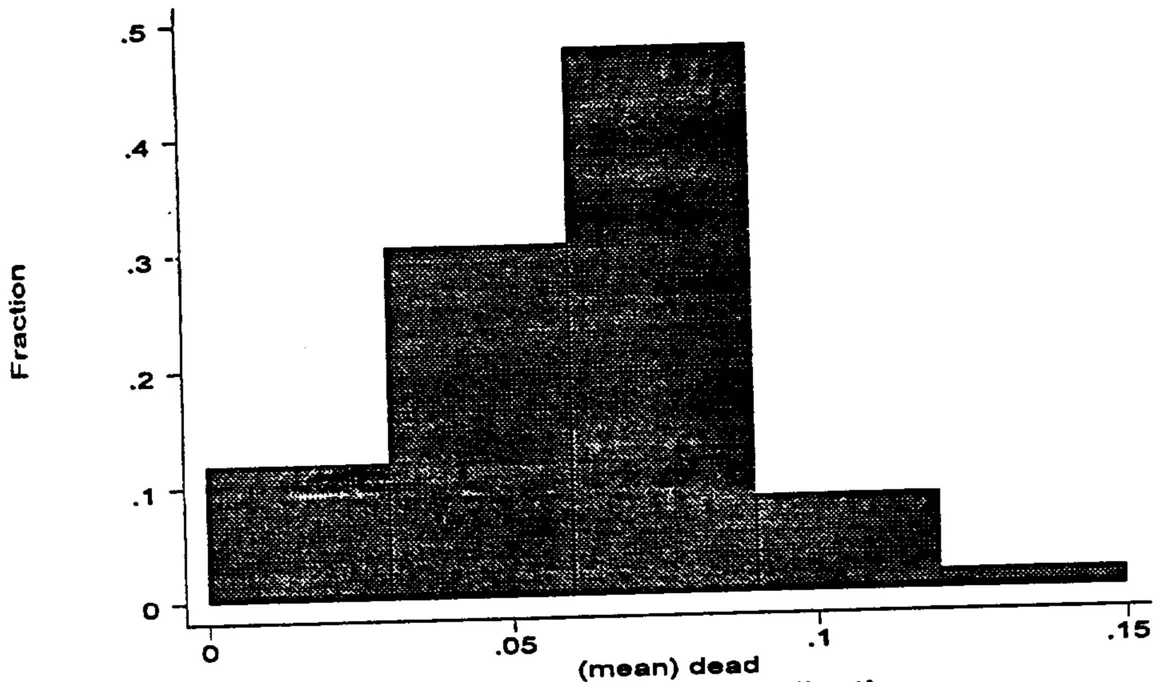
Key:

none

basic

enhanced

FIGURE 4



County-Level Mortality Distribution