THE IMPACT OF INFORMATION TECHNOLOGY ON EMERGENCY HEALTH CARE OUTCOMES

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ABSTRACT

This paper analyzes the productivity of technology and job design in emergency response systems, or "911 systems." During the 1990s, many 911 systems adopted "Enhanced 911" (E911), where information technology is used to link automatic caller identification to a database of address and location information. A potential benefit to E911 is improved timeliness of the emergency response. We evaluate the returns to E911 in the context of a panel dataset of Pennsylvania counties during 1994-1996, when almost half of the 67 counties experienced a change in technology. We measure productivity using an index of health status of cardiac patients at the time of ambulance arrival, where the index should be improved by timely response. We also consider the direct effect of E911 on several patient outcomes, including mortality within the first hours following the incident and the total hospital charges incurred by the patient. Our main finding is that E911 increases the short-term survival rates for patients with cardiac diagnoses by about 1%, from a level of 96.2%. We also provide evidence that E911 reduces hospital charges. Finally, we analyze the effect of job design, in particular the use of "Emergency Medical Dispatching" (EMD), where call-takers gather medical information, provide medical instructions over the telephone, and prioritize the allocation of ambulance and paramedic services. Controlling for EMD adoption does not affect our results about E911, and we find that EMD and E911 do not have significant interactions in determining outcomes (that is, they are neither substitutes nor complements).

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I. Introduction

Over the past two decades, there has been a dramatic increase in the use of information technology (IT) in service organizations. As this phenomenon is often cited as a driver of both economy-wide productivity growth and changes in wage inequality, a wide range of public policies depend on the productivity impact of IT and on the channels through which IT affects productivity (Summers, 2000).

Unfortunately, the benefits arising from the use of IT in service organizations have been notoriously difficult to measure, for several interrelated reasons (Griliches, 1994; Bresnahan and Gordon, 1997). First, IT often provides benefits through improvements in *timeliness* (for example, IT provides quick access to individual account information as well as information about products offered by an organization) and *precision* (products or information provided by the organization may be customized to individuals). While such quality improvements may be reflected indirectly in economic quantities such as rising wages or increased willingness-to-pay for services (factors which may be confounded with price inflation in the context of productivity measurement), few studies provide direct evidence about the role of IT in increasing service sector productivity.

Second, IT is a "general purpose" technology, and the productivity benefits from IT vary enormously, according to the specific application and the characteristics of the adopting organization (David, 1990; Bresnahan and Trajtenberg, 1995; Helpman and Trajtenberg, 1998). Without detailed data about the types and uses of IT, studies of the effects of IT must aggregate over applications where IT has widely different costs and benefits, making it difficult to draw policy conclusions.[1] Even when detailed data is available, productivity estimates based on cross-sectional variation in IT use may be difficult to interpret. For example, organizations employing higher levels of IT may be those who receive higher returns from adopting IT or are otherwise more productive for reasons unobserved to the econometrician, resulting in an overestimate of the average benefits arising from IT adoption (Dinardo and Pischke, 1997; Athey and Stern, 1998).

Third, a variety of theoretical and empirical evidence suggests that IT adoption rarely occurs without related, potentially complementary changes in job design and human

[1] For example, see Brynjolffson and Hitt (1997), Black and Lynch (1998), and Abowd and Kramarz (1999), who confront several challenges in aggregating heterogenous types of IT in their study of the impact of IT on wages and measured productivity growth.

resource practices.[2] Indeed, "skill-biased technical change" is a popular explanation for observed changes in the wage structure;[3] to evaluate the salience of this theory in a specific application, we must establish whether the benefits to potentially skill-enhancing design changes are increasing in IT adoption. Ignoring organizational design not only omits a substantive and policy-relevant contributor to productivity but may also lead to several complex biases in the productivity estimates of the separate impact of IT.[4]

This paper attempts to overcome some of these challenges by examining a specific application of IT. We conduct an empirical analysis of IT adoption and job design in public emergency response systems, commonly referred to as 911 centers. We combine an original survey of IT and job design in 911 centers with a unique dataset of ambulance trips resulting from emergency phone calls, and we use the data to analyze the impact of technology and job design on patient outcomes.[5] This application has several desirable features: (i) the form and use of IT and job design are identifiable and comparable across different 911 centers; (ii) the productivity benefits from this service can be measured in terms of patient health outcomes; (iii) we observe 39 changes in technology and job design during our sample period, allowing us to compare the productivity of 911 centers before and after adoption; and (iv) our sample period includes the middle of the diffusion process, likely reducing the selectivity associated with the adopting population.

In 911 centers, call-takers receive emergency telephone calls, establish each caller's location, and dispatch emergency personnel. Three distinct levels of technology are used in 911 centers. With the lowest level, ("No 911"), citizens can only access emergency

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[2] For example, Milgrom and Roberts (1990) provide a theoretical analysis of complementarity between information technology and organizational design, while David (1991) suggests that complementarity between IT and organizational design is a primary reason why the measured productivity benefits to IT were so low throughout the 1970s and 1980s. See also Bresnahan and Greenstein (1997), who find that newer types of IT are adopted more slowly by firms with higher adjustment costs; Brynjolfsson and Hitt (1997), who empirically analyze the relationship between IT and organizational design in a cross-section of firms; and MacDuffie (1995), Pil and MacDuffie (1996), Hwang and Weil (1996), Ichniowski, Shaw, and Prennushi (1997), and Levy et al (2000) who provide empirical evidence about the relationship between organizational design and (typically IT-intensive) production technology in the context of specific manufacturing industries.

[3] A number of recent papers address this hypothesis, including Berman, Bound, and Griliches (1994), Autor, Katz, and Krueger (1998), Bresnahan (1997), Bartel and Lichtenberg (1987), Kreuger (1993), and Bartel and Sicherman (1999).

[4] See Athey and Stern (1998) for a theoretical analysis of these biases and Bartel (1997) for a discussion of the difficulties inherent in evaluating training program productivity, even within a single organization.

[5] Athey and Stern (2000) perform preliminary cross-sectional analysis using these data, focusing only on technology; this paper provides a much more comprehensive analysis, and further considers the effects on health outcomes of changes in both IT and job design over time.

services by locating and calling the 7-digit telephone number for the appropriate emergency provider. An intermediate level of technology permits access to emergency services by calling 9-1-1 ("Basic 911"). The highest level of technology, Enhanced 911 ("E911"), uses IT to automatically link digital identification from incoming telephone calls to a database containing address and location information. Job design also varies across 911 centers. Some centers use Emergency Medical Dispatching (EMD), in which the call-taker follows a structured protocol to gather medical information, dispatches ambulances according to the priority of the incident, and provides pre-arrival medical instructions (such as instructions for CPR or mouth-to-mouth resuscitation).

Our analysis exploits a unique dataset consisting of ambulance records associated with (nearly) all ambulance rides resulting in emergency hospital admissions in the state of Pennsylvania for the years of 1994 and 1996. In 1991, Pennsylvania enacted legislation facilitating the adoption of both 911 technology and EMD in county 911 centers. During the period of our sample, about half of the 67 counties in Pennsylvania adopt either a more advanced form of 911 technology or EMD, or both.[6] The dataset includes information about the location of the emergency (disaggregated to the level of over 2000 minor civil divisions (MCD)), as well as each patient's health status (e.g., blood pressure, respiration rate, pulse, and suspected illness) as recorded by ambulance attendants upon arrival at the scene of the emergency. Further, the data provide information about subsequent patient outcomes, including diagnoses, billing information such as total charges, (short-term) mortality, and discharge information. To highlight the impact of IT on the timeliness of service provision, we focus on cardiac emergency calls, a group where timeliness is especially important.[7]

By reducing the time between the onset of cardiac symptoms and medical intervention, technology and EMD choices should affect patient outcomes. To assess this, we examine the effect of technology and EMD on indicators of intermediate health status, such as patient blood pressure, upon ambulance arrival. We further calculate a "intermediate health index" (scaled in terms of the probability of survival) that summarizes the health status of the patient across multiple medical indicators at the time

[6] Approximately a third of the sample adopts prior to 1994 and nearly all counties have adopted by 2000.
[7] In focusing on cardiac emergencies, we follow a number of recent studies about medical care output and productivity measurement, such as McClellan and Newhouse (1997) and Cutler, McClellan, Newhouse (1998). See also Triplett (1999).

of ambulance arrival.[8] Since health status is sensitive to response time in the case of cardiac emergencies, the use of this measure allows us to infer the impact of IT and EMD through increased timeliness in emergency response. In addition to employing these measures of health as recorded at the scene of an emergency, we also analyze subsequent patient outcomes such as mortality and total hospital charges.

Using these measures, we evaluate the gains realized by counties who adopt during the time of our sample (in terms of improvements from the pre-adoption levels) and compare these gains to the productivity trend experienced by all the counties in Pennsylvania. To account for heterogeneity within counties in terms of infrastructure, availability and quality of ambulance services, and geography, we include either detailed controls or fixed effects for each of the (on average) 30 MCDs within each county. Our approach can thus be thought of as a "differences-in-differences" estimator measuring the average effect of the 39 county-level 911 changes in technology or EMD observed during our sample. We further employ a variety of approaches to control and test for heterogeneity across counties in terms of the marginal benefits to adopting these practices and the productivity time trend.

Our first set of results establish that the adoption of E911 is associated with significant improvement in the intermediate health index. Relative to a baseline survival rate of 96.2%, we find that E911 adoption leads to a 1% increase in the predicted survival rate. This finding is robust to the use of alternative intermediate health status measures, controlling for EMD adoption (for which we find no measured impact), and employing different comparison groups to estimate the time trend.

Second, we provide evidence that the adoption of E911 can be directly linked to patient outcomes in the hospital, such as mortality and total charges. Of course, these hospital outcome measures are dependent on a large number of intervening (unobserved) factors as well as on the underlying health of patients, and so the relationship between E911 and hospital outcomes is less precisely measured. Our estimates suggest that E911 increases short-term survival rates by about 1%. Finally, we use these estimates to calculate the cost-effectiveness of IT in emergency response systems. Even though the adoption of IT in 911 centers is aimed at a much wider set of emergencies than the

[8] This measure has a non-trivial association with subsequent mortality and is derived from a careful review of the medical literature identifying the relationship between health outcomes and timely response, as discussed in Section IV.

cardiac cases analyzed here (including police, fire, and all other medical emergencies), we find that the benefits to be derived from E911 for cardiac patients alone may cover a substantial fraction of adoption costs.

The remainder of the paper is organized as follows. In Section II, we discuss the institutional details of the pre-hospital emergency response system, describing the adoption process and motivating our empirical approach. Section III describes an economic model of emergency health care production and develops an econometric model to guide our estimation strategy. After a discussion of the data in Section IV, in Section V we compare the characteristics of counties that adopt higher levels of 911 technology during 1994-1996 with counties that adopt before or after our sample period. Section VI presents productivity results. Section VII concludes.

II. Information Technology, Job Design and the Productivity of the Pre-Hospital Emergency Response System

II.A. Emergency Response Systems: An Overview

An Emergency Response System, or 911 system, is 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 was not specialized to emergencies) or to individual service agencies (so that callers needed to locate the telephone number for the appropriate agency). This system often provided inappropriate responses to emergencies (Gibson, 1977; Siler, 1988). Following a model developed in Europe after World War II, the first 911 systems were introduced into the U.S. in 1968. These systems are almost always public.[9]

While the scope and details of systems may vary, emergency response systems typically operate according to the following standard procedure:

- ♦ An individual experiencing an emergency calls a local "emergency" number, either 911 or a designated seven-digit number.
- ♦ The call is answered by a call-taker, who evaluates the caller's emergency and gathers necessary information (including the location and severity of the incident).
- ♦ The call-taker communicates with service agencies for emergency dispatch.

[9] There are a few examples where localities privatize the emergency response system. Indeed, one county (Northampton) attempted to do this in Pennsylvania after our sample period, but this arrangement resulted in an excessively costly system and ended with a protracted lawsuit.

- In some systems, the call-taker may provide additional instructions to the caller.

In some ways, emergency response systems provide benefits that are quite different from most private service organizations.[10] But there are important similarities as well. In particular, 911 systems resemble "help desks" or customer service divisions of corporations, where the help desk industry includes over 100,000 organizations employing over 3 million people.[11] Indeed, industry sources[12] describe the main objectives of help desks as follows: (a) timely response by organizations to customers; (b) provision of precise information or services, tailored to the customer's needs; and (c) effective allocation of scarce organizational resources in responding to customer questions and concerns. In recent years, IT adoption has led to drastic changes in the organization and functioning of help desks across many industries. In particular, as in E911, IT is often used for caller identification and access to customer databases.

Consider the objectives of timeliness, precision, and resource allocation in the context of emergency health care. Timeliness is particularly crucial for cardiac patients: indeed, the first component of the "chain of survival" advocated by the American Heart Association is early access to emergency medical services. Numerous (typically small-sample) clinical studies suggest that the timeliness of administering medical procedures such as CPR and defibrillation has large effects on mortality rates from an out-of-hospital cardiac arrest.[13] Until quite recently, defibrillation – electrical shock therapy to "reset" the electrical activity of the heart in the case of ventricular fibrillation (irregularity) – required equipment which was only available on specially equipped Advanced Life Support (ALS) ambulances, and only a trained paramedic could provide the treatment. If paramedics and ALS ambulances are costly, there will be benefits to gathering precise information about the nature of each emergency, so that the resources will be available for time-sensitive emergencies and will be allocated quickly in those cases. There are

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[10] The timeliness of response to criminal, fire, and medical emergencies can have large effects on outcomes that may affect many individuals. Further, emergency response systems lower the cost to bystanders of providing the public good of reporting emergencies. The use of a uniform number, 911, eliminates the need for citizens to learn the appropriate emergency response number in every locality they visit. Finally, there are efficiency gains to centralizing dispatching services, so that the closest available ambulance can be used. See the web site of the National Emergency Number Association at www.nena.org.

[11] See the web site of Incoming Calls Management Institute of Anapolis, MD, at www.incoming.com.

[12] See the web site of Help Desk 2000, a division of Support Technologies, Inc., at www.helpdesk2000.org.

[13] For example, Larsen et al (1993) find that the probability of survival falls (from a level of .33) at the rate of .023 per minute that CPR is delayed, .011 per minute that defibrillation is delayed, and .021 per minute that an Advanced Life Support (ALS) ambulance response with a paramedic is delayed. See also Lewis et al, 1982; Cummins et al, 1992; Bonnin, Pepe, and Clark, 1993; and Tresch, Thakur, and Hoffman, 1989.

other, indirect benefits to precision as well. For example, there are potentially large costs (such as traffic accidents) associated with an unnecessary "lights-and-siren" response, as documented in a number of studies in emergency medicine (Gibson, 1977; Smith, 1988; Brown and Sindelar, 1993).

II.B. The Role of Information Technology and Job Design

In contrast to many other applications where the choices about IT and job design are difficult to compare across organizations, pre-hospital emergency response systems faced a well-defined set of choices in the 1990s. As described in the introduction, emergency response systems could choose between three different "levels" of IT (No-911, Basic 911, and E911), and they could choose to implement EMD. While there are some sources of heterogeneity within these categories, industry participants in the 1990s recognized these as the primary alternatives.

No-911 systems are typically decentralized, often at the level of a municipality, and the individual service agencies are less likely to use specialized call-taking personnel. In this regard, No-911 can be thought of as both a technological and an organizational choice; we use the word technology for simplicity.

To implement a Basic 911 system, an emergency response system must install dedicated telecommunications services for emergency callers. Basic 911 technology reduces the time between the first awareness of a medical emergency and contact with an emergency agency. As well, the adoption of Basic 911 often involves centralization of emergency response (at the county rather than municipal level), increasing the efficiency of emergency dispatching through specialization. One potential cost to centralization is that call-takers may not be familiar with distant areas, resulting in potential efficiency and precision losses. All Pennsylvania call-takers in Basic (or Enhanced) 911 centers must, by law, receive a minimal level of (fairly) standardized training. Basic 911 may also facilitate the adoption of several related technologies, such as Automatic Number Identification and automatic call recording.

E911 was introduced during the 1980s, and the technology is marketed to emergency response systems by a number of vendors, including several large telecommunication companies (such as the Bell companies, Sprint, and GTE). To implement the Automatic Location Identification features ("ALI") of E911, 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. The databases include precise information about the location of a telephone in a building or public place, and they can also include information about individual health issues or disabilities.

There are a number of benefits to E911 technology. First, 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. The location information is especially useful for callers who are children, adults who do not speak English or are unable to speak, or for cases where people do not know their exact address or directions (the address may be ambiguous in rural areas, or they may be away from home). Furthermore, when address information is communicated instantaneously, the call taker has more time to gather information about the severity of the emergency and 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.

An additional benefit associated with E911 may be in facilitating ambulance dispatch. The mapping system associated with E911 can be used to coordinate with ambulance dispatchers and identify the nearest ambulance. Further, E911 adoption lowers the costs of closely related technologies, such as computer-aided dispatch. In another example, E911 technology facilitates the provision of private emergency response services marketed to the elderly and high-risk citizens.[14]

Alongside these technology choices, emergency response systems also face a distinct choice about job design. For medical emergencies, the low-skill job design involves relatively unstructured call-taking, whereby the call-taker's main responsibility is to provide address information to ambulances. Alternatively, with EMD, call-takers use emergency-specific "protocols," summarized on a set of cards, which guide call-takers through the process of eliciting more detailed information and providing specific emergency medical instructions in response. The call-taker will also provide instructions for preparing the site for ambulance arrival. These interventions have the direct benefit of reducing the time until key medical procedures are performed. EMD may also provide benefits in terms of precision by allowing call-takers to more accurately assess the nature

[14] For example, in some E911 counties in Pennsylvania, subscribers can access an emergency response with wireless technology (e.g., an emergency button). These services exploit the technological features of the E911 system to access location information directly.

and severity of emergencies, and so increase the likelihood of dispatching appropriate equipment.[15] Finally, distressed callers may avoid rash decisions or simply feel better if they receive specific instructions from a knowledgeable person.

The returns to choices about job design and technology may be interrelated. One hypothesis is that E911 and EMD are complementary. For example, E911 automates the collection of location information, allowing for more intensive and effective use of the EMD protocols. Similarly, if higher-skilled workers are required to operate the computers, they may also be better able to implement EMD protocols. A finding of complementarity would support the hypothesis of skill-biased technical change.[16] However, an alternative hypothesis is that E911 and EMD are substitutes. Both E911 and EMD systematize the call-taking process. EMD training may eliminate many of the inefficiencies associated with information gathering by providing a structured protocol for interacting with the caller. Further, EMD allows call-takers to recognize true emergencies very quickly, giving them top priority. A different theory, also consistent with substitution, is that E911 automates the call-taking job, so that lower-skilled workers can perform it. Similarly, we might also suppose that training to use the computer system "crowds out" time and attention for EMD training. The ambiguity present in even such a narrow application highlights the fact that in general, it will be difficult for policy-makers to assess *a priori* whether computer technology is de-skilling or pro-skilling. One goal of this paper is to shed light on this question in a specific example.

II.C. Adoption of IT and Job Design: The Pennsylvania 1991 Public Safety Emergency Telephone Program

To evaluate the returns to technology and EMD, we examine the effects of these policies on health status outcomes in Pennsylvania in the mid-1990s. One possible approach to evaluating the benefits of these policies is to use cross-sectional analyses. However, this approach is subject to familiar biases: for example, E911 may be adopted more aggressively by larger counties, and county size may be correlated with the average

[15] Indeed, the stated goal of EMD is to "ensure that each caller is given the *right help*, in the *right way*, at the *right time*," (Clawson and Dernocoeur, 1998). For example, until recently, a stroke was not considered a time-sensitive event, and EMD protocols typically called for an ambulance to be dispatched in non-emergency mode (without lights and siren), reducing the risk of traffic accidents. Further, ALS ambulances and paramedics can be conserved to be available for true emergencies.

[16] Athey and Stern (1999) analyze adoption patterns of 911 in a national cross-section, and they show that the hours of training required are positively correlated with higher levels of technology, consistent with the hypothesis that advanced levels of technology are associated with more highly skilled workers.

health status of individuals in the counties. An obvious alternative is to exploit time-series variation in the level of IT and/or EMD provided by individual counties. However, even when analyzing within-county changes, potential bias can arise if either the type of change experienced by a county or the date of that change is related to the unobserved incremental returns to the change. For example, the counties that switch between two particular systems may have especially high idiosyncratic benefits to doing so, relative to adopting a different system; further, counties with higher returns may adopt sooner. Although we cannot circumvent these problems altogether, the time period we chose to study has several features that make it more likely that the counties that switch regimes in our sample have returns that are close to the average level of returns.

In late 1991, Pennsylvania passed the Public Safety Emergency Telephone Program ("PSETP"). PSETP reduced the administrative costs and political impediments to adopting both Basic 911 and E911 at the county level.[17] Further, the Act substantially reduced the monetary costs of adoption, in two distinct ways. First, the Act authorized each county in Pennsylvania to implement a telephone tax on its residents to pay for 911 services (between $0.75 and $1.50 a resident depending on the size of the county). Second, the Act divided the State into several EMS regions and authorized and encouraged regional EMS coordinators to increase the level of training and skill investment in 911 centers throughout the state.

As of the beginning of 1993, only five counties throughout the state had implemented both E911 and EMD; by the late 1990s, both were fairly pervasive (only one county in the state still does not have either Basic 911 or E911 in 2000, and EMD is implemented in over 75% of Pennsylvania's counties). Moreover, as discussed in more detail in Section

[17] The Authorizing legislation is explicit about its goals: "The act is designed to provide a toll-free telephone number 9-1-1 for individuals within this Commonwealth to gain rapid, direct access to emergency aid. The number shall be provided with the objective of reducing response time to situations requiring law enforcement, fire, medical, rescue or other emergency service. The authority and responsibility for the creation and implementation of a plan establishing, operating and maintaining adequate facilities for answering emergency calls and dispatching a proper response to a caller's needs shall be vested in the county government. County governments are encouraged to develop and implement a 9-1-1 emergency communication system that will meet the specific needs of the county and take maximum advantage of the integration of communications equipment and personnel to minimize costs and effect a more rapid response to emergency situations. County governments are encouraged to develop enhanced 9-1-1 system plans to the greatest extent possible. The development of county plans that limit the number of PSAPs and dispatch centers to the minimum necessary to meet the guideline requirements and to minimize costs to the public shall be encouraged." See the web site of the Pennsylvania Emergency Management Agency at www.state.pa.us/PA_Exec/PEMA/programs/911/chang120.htm and www.pema.pa.state.us.

V, the period between the beginning of 1994 and 1996 was a crucial adoption period; over half of all counties switched either their level of technology, adopted EMD, or both, during this period. Many of the counties who do not switch during the 1994-1996 period either adopted in the 1991-1993 period or in the 1997-1998 period. Thus, even if the timing of adoption relates systematically to unobserved returns, it may still be useful to estimate the average return to adoption for counties in the "middle" of the distribution of adoption times. Further, our results may shed light on the effects of adopting a state-wide policy, for states with a distribution of counties similar to the middle of the distribution in Pennsylvania.

Since there is no central source of information about 911 and EMD adoption, we surveyed the counties directly, conducting interviews with 911 system managers as well as a variety of industry participants. We also examined industry publications. Although there are some regularities in the adoption patterns of counties (documented in Section V), our interviews supported the hypotheses that PSETP played an important role in facilitating adoption, but that the timing of adoption was largely unrelated to the perceived health benefits. Consider the steps required to adopt E911 (for more detail, see Pivetta (1995)). First, counties must assign new addresses to a substantial fraction of county residents, create new maps, and develop a computerized database. This process is very labor-intensive, and it usually takes more than a year to complete. Moreover, re-addressing requires coordination with local post offices and public utilities, and it further must be approved by each municipality in a county. Prior to the passage of PSETP, municipalities were unwilling to undertake such expenditures themselves and the county had no specific authority to act. Furthermore, the telephone equipment, address 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 that a typical county has a budgeted startup cost of between $1 million and $4 million.[18] Results from our prior work (Athey and Stern, 1999, 2000) suggest that nationally, levels of 911 technology are systematically related to certain

[18] 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 $2.3 million. Its budget comes primarily from a tax on telephone lines ($.97 per line each month) as authorized by PSETP. The Berks County 911 program employs nine call-takers, two administrators, a programmer for its computer-aided dispatching software, and an administrative assistant, which is slightly larger than the average call center in the state according to our interviews in March 2000. For further information, see the Berks County, PA 911 web site at http://www.readingpa.com/911/.)

county characteristics. In particular, the observed patterns suggest that (fixed) adoption costs play an important role in determining 911 levels.[19]

Our interviews suggest that a number factors contributed to the timing of adoption for Pennsylvania counties. In several cases, there were unexpected delays in receiving approval from townships for the new address assignments.[20] In other cases, individual municipalities or local police departments attempted to block 911 adoption, so that they could retain local control (and presumably employment) of call-takers. Finally, scale economies seemed to play a central role in determining the very first and very last adopters, outside our sample period,[21] but size and other demographic factors were less important in determining the order of adoption for the remaining counties.

In terms of EMD adoption, several EMD vendors responded to the statewide training initiatives, which were implemented at the level of the EMS region, by focusing marketing efforts on one EMS region at a time. For example, more than half of the counties in Regions 1 and 4 adopted EMD relatively early in our sample period, although these two regions have otherwise quite different characteristics.[22]

Finally, in our survey and in interviews with 911 system managers, we explored the possibility that other changes in the 911 system, or the health care infrastructure, might confound our analysis of technology adoption and EMD. One potential concern is that counties changed their ambulance system during the sample. However, we found that each of the following elements of the ambulance system changed for at most one county during our sample: the number of assigned ambulances, the ambulance composition (ALS

[19] Athey and Stern (1999, 2000) performed cross-sectional analyses of 911 technology using a national sample of about 800 911 systems in 1995 with county-wide coverage. We found that higher levels of 911 technology were associated with a larger scale (measured in terms of call volume or overall population), consistent with the theory that fixed costs play an important role in adoption. Higher technology was also positively correlated with higher population density, despite the fact that we might hypothesize higher returns in rural areas, where addressing is less systematic (the costs of adoption are higher as well, potentially reconciling this finding). Per-capita income did not play a significant role, but political factors, such as voting patterns, did impact adoption.

[20] Such delays often involved negotiations between the municipalities and counties on peripheral issues. For example, one respondent reported that E911 adoption was delayed over negotiations with a municipality over the provision of state police for highway patrol.

[21] One respondent in a smaller county justified slow adoption by suggesting, "When someone has an emergency, they know to call me! They know the number."

[22] Region 1 is Southwest Pennsylvania (including areas surrounding Pittsburgh), while Region 4 is north-central; these areas are very different from one another (relative to the variation in our sample) in terms of geography and demographics, as Region 4 is less densely populated.

or BLS), and the ownership or organization of the system.[23] A second concern is that 911 systems might have changed their overall organization at the same time that E911 was adopted, making it difficult to separate out the role of technology. Indeed, while centralization or the opening of a completely new facility is quite common among the adoptors of Basic (five counties report that the switch from No 911 to Basic was coincident with additional centralization), only four out of twenty-three E911 adoptors report a centralization change during the sample period. Finally, we did not find evidence that the call center management changed at the same time that E911 was implemented. In the cases where a new "911 Coordinator" was hired for the E911 system, the individual typically began working at least six months before the E911 system went into effect.

III. The Empirical Framework

III.A. The Production Function for Health Status

We use measures of the health status of cardiac patients to assess the productivity of 911 technology and EMD. Consider first 911 technology, where we focus on two distinct questions. The first concerns the direct relationship between IT and response time. When health status is used purely as a measure of timeliness, we focus on intermediate health status measures that are observed at ambulance arrival (measures that should deteriorate over time), without necessarily relating these measures to eventual outcomes (although we do use survival rates to scale the measures). The second question concerns the welfare benefits to 911 systems in terms of longer-term health outcomes. Though these benefits accrue as a direct result of improvements in timeliness, timeliness may not be critical for the group of patients who will die anyway. Further, the effects of timeliness may be difficult to measure for patients likely to survive: the benefits may not be apparent immediately, and longer-run outcomes are confounded by a variety of intervening treatments.

Guided by these concerns, we develop a simple model motivating our empirical approach. A patient's health status is determined by a variety of components, including blood pressure, pulse, and respiration. Let h_l denote the status of component l, l=1,..,L,

[23] While there is tremendous heterogeneity in terms of whether ambulances are public or private and in terms of how concentrated ownership is, we found no examples of a county that switched its underlying organization during our sample period and that also changed its 911 technology and/or EMD. As an additional robustness check, in our empirical analysis, we calculate and control for the number of distinct ambulances that served an MCD each quarter.

and let $\mathbf{h}=(h_1,..,h_L)$. The patient's true health status is $H(\mathbf{h})$. At time $\tau=0$, a patient experiences an incident involving cardiac distress. The initial severity of this incident (taking into account the patient's underlying health status) is determined by ξ, where higher values correspond to better health. The ambulance arrives at time $\tau=\tau^A$. The status of component l at time τ is given by $h_l(\tau,\tau^A,\xi)$. Faster response time weakly improves health status: for $\tau>\tau^A$, h is nonincreasing in ambulance arrival time τ^A, while h_l is unaffected by τ^A for $\tau\le\tau^A$. If h_l is nonincreasing in τ in the relevant range, then $h_l(\tau^A,\tau^A,\xi)$, the status at ambulance arrival, is nonincreasing in τ^A: when the ambulance arrives more quickly, the patient is observed in a healthier state. While τ^A is unobserved within our dataset, if a 911 center adopts a technology such as E911 which is both uncorrelated with initial severity (ξ) and reduces τ^A, then, all else equal, $E[h_l(\tau^A,\tau^A,\xi)]$ will be higher in counties with E911.[24]

Now consider the welfare effects of 911 technology. Define the reduced-form health status function $\tilde{H}(\tau,\tau^A,\xi) = H(\mathbf{h}(\tau,\tau^A,\xi))$. Fix some time τ^F (e.g. 48 hours after the incident occurs). For simplicity, suppose that the value of a patient's health status at time τ^F, $\tilde{H}(\tau^F,\tau^A,\xi)$, is a sufficient statistic for the patient's long-term outcome. Normalize $\tilde{H}$ so that if $\tilde{H}(\tau,\tau^A,\xi)\le 0$, the patient dies.

Figure A plots $\tilde{H}$ as a function of τ for different values of ξ and τ^A. The shaded areas represent the overall health benefit to patients from faster ambulance response time. Ideally, we would measure the welfare effect of faster response time by taking an average (potentially weighted by the implied quality of life) of these health benefits. However, we do not have accurate measures of health status at τ^F. Thus, consider approximating the welfare effect by measuring the change in the probability of survival until τ^F. Observe that in the figure, there are three groups of patients. For the first group, the initial health level ξ_H is so large that, for all τ^A in the relevant range, $\tilde{H}(\tau^F,\tau^A,\xi_H)>0$. For the third group, the initial health level ξ_L is so small that, for all τ^A, $\tilde{H}(\tau^F,\tau^A,\xi_L)=0$. For the middle group, τ^A affects whether or not the patient is alive at time τ^F.

The probability of survival until τ^F is probably a conservative estimate of the benefits of reduced response time because reduced response time improves the long-term health outcomes of the patients who survive and because the measure assigns zero benefit

[24] As discussed below, since our empirical approach is based on changes in 911 technology rather than cross-sectional comparisons, this assumption is stronger than required.

to prolonging life for patients who die before τ^F; however, the measure does not account for the fact that some patients may die shortly after τ^F. In practice, we use six-hour and forty-eight hour mortality; the health care literature suggests that mortality rates decline sharply over the first few hours following the incident.[25] Finally, note that in practice, the measure is confounded by the myriad interventions and treatments which occur after the ambulance arrives, each associated with additional uncertainty. Thus, in evaluating welfare benefits, it may be useful to take into account our first measure, the effect of E911 on health status at ambulance arrival. As we noted in Section II.A, the clinical emergency medicine literature has documented the longer-term health benefits of early response.

Finally, consider assessing the benefits of EMD using these measures. One benefit of EMD is to conserve resources for true emergencies; since cardiac symptoms are high priority, EMD may (indirectly) reduce response time. Second, EMD may have direct health benefits, beginning at some time $\tau \in (0, \tau^A)$. Although we may detect these benefits at the time of ambulance arrival, the overall benefits of EMD probably continue to accrue over time (similar to the effects of reducing τ^A). Thus, the probability of survival until τ^F may incorporate a greater fraction of the effect of EMD.

III.B. The Estimation Strategy

This section formalizes our approach to estimating the effects of technology and training on health outcomes, and it interprets the required econometric assumptions in terms of our application. Consider the following notation, where Roman variables are observed and Greek variables are unobserved:

<u>Notation</u>	<u>Interpretation</u>
(t,i,j,k)	Date t, county $i \in \{1,..,I\}$, MCD $j \in \{1,..,J^i\}$, patient $k \in \{1,..,K^{ij}\}$.
$y^t_{i,j,k}$	Observed health outcome of patient (t,i,j,k).
$\mathbf{x}^t_{i,j,k}$	Observed patient and incident characteristics for patient (t,i,j,k).
$\mathbf{z}^t_{i,j}$	Observed MCD characteristics for MCD (i,j) at date t.
c_i	Dummy variable for county i.
d^t	Dummy variable for calendar date t.
χ^t_i	Unobserved 911 center quality and characteristics of county i at date t.

[25] See, e.g., Herlitz et al (1995). We also caution that for some patients, increased short-term survival may lead to high medical expenditures; see Meltzer (1997).

$\psi_{i,j}^{t}$	Unobserved MCD characteristics (i.e. geography and infrastructure).
$\xi_{i,j,k}^{t}$	Unobserved incident severity.

In our sample, some counties maintain the same level of technology and training throughout the time period, while others switch during the time period. The following notation is used to keep track of which counties switch and the type of switching (counties experience up to three systems in our sample, but for simplicity, here we introduce notation for two systems only).

Notation	Interpretation
$\mathbf{s}_i^t$	Indicators for technology-EMD systems (county *i*, date *t*).
A_i, B_i	Technology-EMD systems experienced by county *i*, in order of date.
R_i	"Switching type" of county *i* (the (A_i,B_i) pair).
$\overline{d}_i$	Switching date of county *i* (set arbitrarily high for non-switchers).

Using this notation, a patient's health outcome can be written:

$$y_{i,j,k}^{t} = f(\mathbf{s}_i^t, d^t, \mathbf{x}_{i,j,k}^t, \mathbf{z}_{i,j}^t, \xi_{i,j,k}^t, \chi_i^t, \psi_{i,j}^t)\,.$$

Our estimation approach is based on "differences-in-differences." Consider the assumptions that validate this approach. First, we decompose county quality into a time-varying component and a fixed component, and assume that the time-varying component is additive and constant across counties:

(A1) $\chi_i^t = \mu_i + \nu^t$.

In Section VI.B.4, we relax this assumption by allowing the time trend to vary with observable characteristics of the county or MCD. A more subtle possibility is that the time trend differs across counties, and this is correlated with the level of 911 system chosen by the county. An indirect test of this hypothesis is that the time trend differs across 911 systems, among the non-switching counties; we test this in Section VI.B.4.

Now consider the relationship between the unobservables and the 911 system. Some counties may have higher levels of response times (due to features such as geography and infrastructure), and these may be correlated with the 911 system (for example, some counties face political constraints that affect the provision of other public goods, and these goods affect the average response time in the county. We allow for this possibility; however, we assume that the *incremental returns* to adopting different 911 systems are the same across counties and MCDs (i.e. E911 saves 30 seconds in every county), and further, *f* is additively separable in χ_i^t and $\psi_{i,j}$. Formally:

$$\text{(A2)} \quad y_{i,j,k}^t = \tilde{f}(\mathbf{s}_i^t, d^t, \mathbf{x}_{i,j,k}^t, \mathbf{z}_{i,j}^t, \xi_{i,j,k}^t) + \psi_{i,j} + \chi_i^t$$

Without (A2), our approach will identify the average returns among counties that change their 911 systems during the sample period (which, we argue, may not be very different from the population average in our application). Next, consider restrictions on unobserved patient severity. We allow for the case where the 911 level or the switching regime is correlated the average health of patients in a county; however, we assume that any changes in patient health over time are unrelated to the switching regime. Formally:

(A3) $\xi_{i,j,k}^t$ is independent of R_i and $\bar{d}_i$ conditional on $(c_i, \mathbf{z}_{i,j}^t, \mathbf{x}_{i,j,k}^t)$.

Because higher levels of technology and training are more common later in the sample, it is critical that we control for calendar time. The time trend is identified in our sample without parametric restrictions, in part because our sample includes "non-switching" counties:

(A4) For some counties *i*, $\mathbf{s}_i^t$ does not change with *t*.

The switching dates for the counties in our sample vary continuously, so that (A4) is not strictly necessary, but conceptually (A4) highlights the idea that the non-switching counties serve as a "control group" for the improvements over time that counties would experience in the absence of adoption of technology or EMD.

If unobserved county quality is correlated with the county's system, a cross-sectional regression will not give consistent estimates of $\boldsymbol{\alpha}$. An obvious alternative is to use county fixed effects. Under conditions (A1)-(A4), the average effect of *changes in* $\mathbf{s}_i^t$ on $y_{i,j,k}^t$ are identified. We refer to assumption (A1)-(A4) as "the assumptions of the fixed effect model." For estimation, we impose a linear functional form for $\tilde{f}$. The following estimating equation is stated in terms of differences, where Δ_i represents the difference between a variable and its mean value in county *i*, and κ_i is a constant for county *i*:

$$\text{(E)} \quad \Delta_i y_{i,j,k}^t = \kappa_i + (\alpha_{B_i} - \alpha_{A_i})\mathbf{1}\left\{t > \bar{d}_i\right\} + \Delta_i \mathbf{x}_{i,j,k}^t \boldsymbol{\beta} + \Delta_i \mathbf{z}_{i,j}^t \boldsymbol{\gamma} + \delta^t + \Delta_i \xi_{i,j,k}^t$$

The functional form incorporates the implicit assumption that the benefits of different 911 systems are constant across counties. Of course, it is possible to include and test for interactions with observable exogenous variables.[26] Another implicit restriction of this baseline model is that there are no learning effects, which we address Section VI.B.1 by allowing $\boldsymbol{\alpha}$ to vary with the time from the adoption date.

III.C. Hypothesis Tests

We use the model of Section III.B for three objectives: (i) to test hypotheses about the returns to adopting technology and training; (ii) to test assumption (A2); (iii) to test hypotheses about the nature of the interaction between 911 technology and training.

Number the possible systems experienced by the county using two digits, where the first is the level of technology and the second is the EMD level. For example, 00 indicates no 911 and no EMD, 10 indicates basic 911 and no EMD, 11 indicates basic 911 and EMD, 20 indicates E911 and no EMD, etc. Suppose for the moment that no counties have EMD. Then, the returns to technology adoption are given by the contrasts $\Delta\alpha_{10} \equiv \alpha_{10} - \alpha_{00}$ and $\Delta\alpha_{20} \equiv \alpha_{20} - \alpha_{00}$. These contrasts are identified directly from the estimating equation (E).

As well, we test (A2). Recall that our sample contains three groups of counties that switch technology: counties switch from no 911 to basic 911, from no 911 to E911, and from basic 911 to E911. Observe that the contrast $\Delta\alpha_{10}$ is identified by estimating (E) using the first group (with a control group of counties that do not switch); similarly, the second group identifies $\Delta\alpha_{20}$, and the third group identifies $\alpha_{20} - \alpha_{10} \equiv \Delta\alpha_{20} - \Delta\alpha_{10}$. Thus, the model is over-identified with respect to the parameters of interest. This suggests an initial test of the model: relax and test the cross-equation restriction on the benefits to switching in each group of counties implied by (A2). To do so, we let λ_{B_A} represent the contrast parameter in a county that experiences a shift from system *A* to system *B*; the contrast parameters can be estimated using county fixed effects, analogous to (E). Since $\hat{\lambda}_{10\_00}$ provides an estimate of $\Delta\alpha_{10}$, $\hat{\lambda}_{20\_00}$ provides an estimate of $\Delta\alpha_{20}$, and $\hat{\lambda}_{20\_10}$ provides an estimate of $\Delta\alpha_{20} - \Delta\alpha_{10}$, we can simply test the hypothesis that $\hat{\lambda}_{20\_00} - \hat{\lambda}_{10\_00} = \hat{\lambda}_{20\_10}$. Under the alternative hypothesis that different groups have different incremental returns, and these unobserved returns are correlated with the 911

[26] More generally, the model is still identified if unobserved variables interact with the 911 switching regime and date, so long as these variables are independent of the switching regime and date conditional on the other observables (for example, for the case of unobserved severity, under (A3)).

switching regime or date, we will find $\hat{\lambda}_{20\_00} - \hat{\lambda}_{10\_00} = \hat{\lambda}_{20\_10}$ only if the selection biases that arise for each regime are exactly offsetting.[27]

Next, consider the problem of identifying interaction effects between technology and training. Recall that by definition, technology and training are *complements* in increasing IHS, if and only if $\alpha_{21} - \alpha_{11} \geq \alpha_{20} - \alpha_{10}$, $\alpha_{21} - \alpha_{01} \geq \alpha_{20} - \alpha_{00}$, and $\alpha_{11} - \alpha_{01} \geq \alpha_{10} - \alpha_{00}$. Since each term in these inequalities involves a contrast, all of the parameters required to test for complementarity are identified from our fixed-effects model. However, despite the fact that our identification strategy is based on *within-county* changes, the identification of an interaction effect exploits both cross-sectional and time-series variation. To see this, observe that each county in our sample experiences only two or three systems, while each inequality involves the returns to four different systems. Despite this, the assumptions of our fixed-effects model are sufficient to identify estimates of the interaction effects among training and technology. Recall that (A2) rules out unobserved incremental returns to the 911 systems (more generally, any such unobserved incremental returns should be independent of the switching regime and date). In that case, it is valid to compare the estimated contrast parameters across counties.

IV. The Data

IV.A. Data Sources

To explore the impact of IT and skill-oriented job design on health care outcomes from the pre-hospital emergency response system, we exploit (and build upon) an unusual dataset assembled by the Pennsylvania Department of Health, Emergency Medical Services Office ("PA EMS"). The PA EMS dataset records detailed information for all emergency incidents in Pennsylvania for which (a) an ambulance responded to the emergency; (b) the dispatch resulted in a hospital admission; and (c) the ambulance record and the hospital record, which are not directly linked at the time of hospital admission, could be matched based on patient and incident identifying information in both records. In a given year, the PA EMS dataset consists of over 100,000 ambulance

[27] A second alternative hypothesis is that the returns to adoption depend on the path taken (i.e. adopting EMD first, then E911, leads to different results than proceeding in the opposite order). While we cannot distinguish between these two hypotheses statistically, our interviews with industry participants and reading of the industry literature lead us to believe that such path-dependence hypothesis is not likely in this application. Thus, we focus our interpretations on the first alternative.

rides matched to hospital admissions (out of an annual total of approximately 1.7 million hospital admissions in Pennsylvania). For each patient, we observe the following:

- Incident location (the MCD) and time of day;
- The timing and nature of emergency response (e.g., the time between dispatch and arrival at the incident scene, whether the response was in "lights-and-siren" mode, the vehicle number of the ambulance, and the certification level of attendants);
- Health indicators upon the arrival of EMS workers at the incident scene (e.g., blood pressure, pulse, respiration, and suspected illness);
- Post-incident arrival emergency procedures and transport (e.g., whether transport to hospital is in "lights-and-siren" mode, what treatments were provided enroute to the hospital);
- A (confidential) code for the hospital to which the patient is transported;
- Diagnostic information at the time of hospital admission;
- Hospital discharge and billing information (whether the admission results in a fatality, charges disaggregated by type and procedure, insurance status of the patient, and patient billing zip code).

We focus the bulk of our analysis on the relationship between intermediate health status, as measured at the incident scene, and the level of IT and EMD in the county in which the incident occurs. To accomplish this, the PA EMS dataset is supplemented with additional data providing information about the pre-hospital emergency response infrastructure in each county throughout time, and demographics associated with the county and MCD where the incident occurs.

Specifically, we supplement the PA EMS dataset with data gathered from a retrospective survey conducted by the authors in March, 2000 and confirmed in a follow-up survey in July, 2000 (See Appendix C for the full "MIT 911 Survey"). For each county-level emergency response agency in Pennsylvania, we identified an individual (typically, the 911 coordinator) with knowledge of the history of technology and EMD adoption within the county. In nearly all cases, respondents were able to provide information about adoption dates within a confidence interval of at most a month or so (most were able to provide an exact "day" in which a particular technology or training program was "turned on").[28] The survey results therefore provide both the 911

[28] The initiation of either a higher level of 911 technology or EMD seems to have been a pivotal event in the history of most call centers (for a particularly riveting account, see, www.ccia.com/~lawco911/index.html); typically, respondents provided detailed descriptions of the factors that delayed adoption (mostly political in nature) and the perceived benefits associated with adoption.

technology and EMD levels associated with a given county at a given point in time in our sample period.

In addition, we incorporate additional data (at the zip code, MCD, hospital, and county levels) as available from various Census Bureau publications (City and County DataBook, Census of Governments, Gazetteer), as well as daily weather data available from the National Climatic Data Center.

IV.B. Sample Selection

We refine the dataset to focus on a population that allows us to highlight the relationships between 911 technology, EMD and health care outcomes. First, we select only patients with diagnoses of cardiac conditions (such as acute myocardial infarction, cardiac dysrhythmias, and heart failure), for whom timeliness is particularly important. Further, to ensure comparability across the two years and keep only ambulance rides most likely dispatched from a 911 call center, we eliminate observations satisfying one or more of the following criteria (our core results are robust to the inclusion or exclusion of any single group):

- All emergencies which do not require "lights-and-sirens" on both the outgoing dispatch call and during the ambulance transport to the hospital;
- All patients less than 20 years old and all pregnancies;
- Transports from one medical facility to another;
- Incidents in the two large metropolitan areas of Pennsylvania, Philadelphia and Pittsburgh;[29]
- Incidents where response time to the incident scene, time at the incident scene, or time from the scene to the hospital is greater than one hour;
- Incidents where less than $50 of hospital charges are incurred.

After eliminating observations for which either the incident county is missing or one of the key health status measures is missing, our final dataset consists of 16,725 observations, about evenly divided between 1994 and 1996.

[29] Our choice to exclude Philadelphia and Pittsburgh is motivated by the fact that (a) neither of these municipalities experienced adoption during our sample period (and so their inclusion would only affect the composition of the control group) and (b) it may be possible that the productivity trend in extremely dense urban areas is significantly different than that experienced by light urban, suburban, or rural areas.

IV.C. Variables and Summary Statistics

This section introduces our health status outcome measures, the emergency response system measures, and the demographic characteristics of the sample. Table 1 provides variable names and definitions; Table 2 reports summary statistics.

IV.C.1. Health Status Outcome Measures

Our analysis employs a number of different health outcome measures available from the PA EMS dataset, which vary along two dimensions. First, our health outcome measures differ with respect to *when* they are measured relative to the onset of the emergency incident. Following our discussion in Section III, we refer to measures observed at the time of ambulance arrival as measures of intermediate health status, while measures observed after hospital admission, such as mortality and hospital charges, are referred to as hospital measures. Second, some of our measures are "raw" indicators of factors such as blood pressure and mortality; others are constructed, including "health indices" that aggregate the raw intermediate health status measures.

Raw Patient Health Outcome Measures

Our raw measures of intermediate health status, recorded at the incident scene, include systolic blood pressure (BLOOD PRESSURE), the rate of respiration (RESPIRATION), pulse rate (PULSE), and the Glasgow coma score (GLASGOW).[30] Each of these measures are consistently and unambiguously recorded in our dataset for both sample years, and they reflect distinct components of health for cardiac patients.[31]

In addition to raw measures recorded at the incident scene, we also observe several hospital stay characteristics, including the time and date of admission and discharge, the discharge status, and the total charges accrued by the patient. Since these data are available *only* for the first hospital to which the patient is admitted, we use the hospital

[30] While the first three measures should be relatively self-explantory, the Glasgow Coma score (also referred to as the Glasgow trauma score) is somewhat more specialized to emergency medicine. This score ranges from 3-15 (with increasing scores indicating lower severity) and reflects patient alterness and responsiveness along three dimensions: eye response, verbal response and motor response. For example, if a patient exhibits no eye opening together with no verbal or motor response, the patient would receive a score of 3, suggesting life-threatening conditions (see www.trauma.org).

[31] The PA EMS data also records several other measures which we do not exploit here, including EKG indications and indicators of various pre-hospital treatments (defibrillation, CPR, and medications). Many of these treatments are only available on ALS ambulances, and so may not have been available to all patients. Because our policies of interest may affect ALS ambulance allocation, the availability of these treatments may not be exogenous.

outcome data with caution. Specifically, if (a) the patient is transferred from the initial admitting hospital to a more advanced hospital with cardiac facilities or (b) the patient if discharged and readmitted in a short amount of time, our data will record these patients as discharged to hospital and home, respectively, and will not provide information about their future health outcomes.[32] For this reason, in calculating hospital measures, we restrict attention to "medium-term" survival: 6 HR SURVIVAL (mean = .99) and 48 HR SURVIVAL (mean = .962). We expect that the effects of pre-hospital care may be most pronounced during the initial hours following an incident (see, e.g., Herlitz et al (1995)), and that such medium-term measures likely reduce the censoring biases described above.[33] Further, though recognizing the long list of caveats associated with its usage (see Berndt, et al, 1998), we also incorporate incurred inpatient charges (TOTAL CHARGES). Similar to previous studies which have analyzed hospital charges (e.g., McClellan and Newhouse, 1997), we find that the distribution of charges is extremely skewed, with average charges just below $14,000 and a standard deviation of almost $17,700.

Calculated Patient Health Outcome Measures

To analyze the relationship between health status and 911 technology and job design, we convert the raw health outcome measures described so far into a set of indices of patient health, building on our discussion in Section III. The index (a) accounts for non-linearities or non-monotonicities (as identified by the clinical emergency medical literature) in the relationship between the raw measures and patient health; (b) aggregates the individual measures into a single index which distinguishes among patients more finely; and (c) provides an explicit link between health measures recorded at the incident scene and patient mortality.

The clinical emergency medical literature includes a large body of research devoted to developing useful "scores" of patient health based on various intermediate health status measures. These scores are used to guide medical decision-making and to provide

[32] Indeed, in our sample, patients are about 10 times more likely to transfer if their admitting hospital does not have facilities such as cardiac catheterization laboratories or open-heart surgery facilities. We have completed some preliminary exploration disentangling different types of hospital discharges, discussed further in Table 8B.
[33] Only .7% of our sample transfers to another hospital within 6 hours, while 5.3% transfers within 48 hours.

objective benchmarking tools for comparing different hospitals and health care systems.[34] For any given scoring method, one or more health measures are categorized into ranges, with each range being assigned a number; the score is a weighted average of these score components. Since we have been unable to identify a single "best" scoring system for our specific patient group (all cardiac diagnoses, with vital statistics measured upon ambulance arrival), our approach is to construct several measures modeled after leading scores designed for critical care assessment, but where our score is based on four raw measures of intermediate health status included in our dataset.[35]

We begin by creating two indicator variables based on whether a patient is in the "low-risk" region in terms of a single health measure: LOW-RISK BLOOD PRESSURE (equal to 1 if systolic blood pressure is greater than 90) and LOW-RISK PULSE (equal to 1 if the pulse rate is greater than 40). While these measures are correlated with each other, they are distinct: the correlation coefficient is only .34, and LOW RISK BP includes more patients (the sample mean is less than .9).[36]

Second, we calculate two measures of intermediate health status, $HINDEX_1$ and $HINDEX_2$. In $HINDEX_1$, we first create a set of categories for each of our four raw health measures based on (a) the critical cut-off points for BLOOD PRESSURE, RESPIRATION, and GLASGOW suggested by one leading scoring system (called the Revised Trauma Score (RTS) system) and (b) employ a cut-off for PULSE used in several alternative scoring systems.[37] We then perform a probit regression of 48 HOUR SURVIVAL on the full set of these categorical variables (reported in Appendix A).[38]

[34] A fair assessment of this extremely voluminous literature and the debates about the efficacy of different scoring methods cannot be undertaken here. However, see *The Medical Algorithms Project*, developed by John R. Svirbely, M.D., & M.G.Sriram, Ph.D., at www.medal.org for a survey and further references.

[35] Scores at specific diagnoses such as cardiac emergency tend to be designed for use once the patient has arrived *at the hospital*; as well, while our dataset is composed of all cardiac emergencies, several scores are tailored to more narrow indications such as cardiac arrest.

[36] We also have experimented with alternative cut-off points for these measures as well as alternative "low-risk" measures using GLASGOW and RESPIRATION. For example, we used the categories suggested by the Simplified Applied Physiology Score (SAPS) (LeGall et al, 1984, 1993); however, as with many other scores we found, we cannot apply SAPS directly because it requires indicators of health that we do not observe. Overall, our results are robust to variation in the specific type of health measure used in the analysis.

[37] PULSE is not included among the measures in the RTS system. However, we found this measure to be correlated with mortality, and alternative scoring systems did in fact use PULSE, so we chose to include it in our analysis.

[38] Overall, the results from this mortality regression are sensible from the perspective of the clinical literature. While there is of course a high degree of multicollinearity among the indicators, key indicators are significant predictors of survival (e.g., CAT4(GLASGOW), CAT4(BLOOD PRESSURE) and LOW

$HINDEX_1$ is calculated as the predicted value of 48 HOUR SURVIVAL from this regression (its mean is equal to .962, equal to the sample survival probability).

As a robustness check, we compare our results about $HINDEX_1$ to those derived using the RTS directly (this score is based on BLOOD PRESSURE, RESPIRATION, and GLASGOW); although this score is not designed for cardiac patients, it has the advantage that our data includes all of the elements required for the score.[39] To make the RTS interpretable within our sample, we first perform a probit regression of 48 HOUR SURVIVAL on RTS (reported as well in Appendix A) and then calculate $HINDEX_2$ as the predicted survival probability from that regression. Thus, $HINDEX_2$ is simply a monotonic transformation of the RTS, scaled by the relationship between survival and this score within our sample.

Both $HINDEX_1$ and $HINDEX_2$ can be interpreted as the 48-hour survival probability of a patient, conditional on (a) their health status at the time of the arrival of an ambulance and (b) the patient receiving an "average" level of care subsequent to the arrival of an ambulance. Not surprisingly, given their construction, these two measures are highly correlated with each other (.9623).

Finally, in terms of calculating subsequent health outcome measures, we combine our information about mortality with TOTAL CHARGES to create an indicator variable for a POOR OUTCOME. This measure is equal to 1 if the patient dies prior to being discharged from the hospital or if TOTAL CHARGES exceed $20,000.

IV.C.2 County-Level Emergency Response System Measures

We divide the information technology of counties into three tiers: NO 911, BASIC 911, and E911.[40] By the end of the sample 47 out of 65 counties have adopted the E911

RISK PULSE). As well, the negative coefficient on CAT3(RESPIRATION) accords with the clinical literature's contention that the respiration cut-off is nonmonotonic (survival is predicted to be lower for extremely low respiration (such as in CAT1) and extremely high respiration rates (such as in CAT3). As well, the overall explanatory power of the regression is reasonable (pseudo r-squared = .2)

[39] However, one disadvantage of the RTS is that it is designed primarily for trauma patients and so places a relatiely high weight on GLASGOW, which accounts for patients with head trauma not affecting other vital signs. As such, this precise measure may not be as appropriate for cardiac patients. It should be emphasized, however, that while the use of a skewed weighting scheme may lead to a noisy measure of health, it should not create a bias in favor of finding an impact from 911 technology and job design.

[40] In order to be classified as BASIC on a particular date, a county had to have established a dedicated 911 telecommunications service for emergency callers in their counties; in most cases, this was also associated with ANI technology as well. In order to be classified as E911 on a particular date, a county had to have

technology (and comprise 78% of the observation patient-level sample). On the other hand, 19 counties begin the sample with NO 911 (of which 5 shift to BASIC and 7 shift to E911 between the beginning of 1994 and the end of 1996), comprising 25% of the patient-level sample. Finally, out of the 20 counties which begin the sample at the BASIC level, 13 of these counties adopt E911 during the sample period; along with the counties that move from NO 911 to BASIC 911, 17% of the total sample is observed using the BASIC technology.

We code the job design of a given county with a dummy variable for EMD.[41] Out of 43 counties that did not have EMD at the beginning of 1994, 21 of these counties adopt EMD during the 1994-1996 sample period; the patient sample is just about evenly divided between emergencies under EMD and those which occur without EMD.

IV.C.3 Patient Characteristics and Incident Location Demographics

While our estimation strategy relies primarily on a differences-in-differences approach with fixed effects for each MCD, we also employ a number of additional controls for patient health quality and emergency infrastructure heterogeneity using observed individual patient characteristics and incident location demographics. In terms of patient characteristics, we observe the sex, age, and health insurance type of the patient, and we infer their home zip codes from the zip code used for health care billing purposes (recall that many emergencies occur in locations other than the primary residence of the victim). Perhaps not surprisingly, the mean age of cardiac emergency patients is relatively old (70.3) with the consequence that over two-thirds of all patients are covered by Medicare (and less than one percent are reported as self-insured). Using the patient billing zip code, we incorporate several zip code-specific measures available from the U.S. Census (each of these variables is denoted with the prefix ZIP_).[42]

In addition, we calculate several incident location demographics measures. These variables differ both in terms of their level of aggregation (at the MCD level, we use the prefix M_, while at the county level we use the prefix C_) as well as whether there is

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implemented an Automatic Location Identification technology and more than 50% of the county's addresses needed to be successfully addressed and available to the ALI system.

[41] In order for a county to have adopted EMD by a given date, EMD training and certification must be mandatory at the call center and one of the approved EMD protocols must be in use at the call center for medical emergencies.

[42] For zip codes for which demographic information was not available, we use a dummy variable indicating tht the zip code data was missing.

variation across time within a given geographic region.[43] At both the county and MCD level, we include a number of (relatively standard) demographics reflecting size, wealth, and density (POPULATION, DENSITY, and PERCAP INCOME), the distribution of which we explore in some more detail in the next section when we consider the potential selectivity of adoption during our sample period.[44] We also included daily weather data from readings at over one hundred Pennsylvania weather stations, where each MCD is matched with the closest weather station.

As well, we construct additional incident location measures directly from the PA EMS dataset. For each county and MCD, we calculate the TOTAL PATIENTS observed in the data (i.e., the total number of emergency incidents (cardiac and otherwise) which occur in that county or MCD during the sample period are for which an ambulance record has been matched with a hospital admission record). Similarly, we calculate the number of distinct ambulances serving each county or MCD, constructing both the aggregate number (TOTAL # AMBULANCES) and the number specifically equipped with ALS capabilities (TOTAL # ALS AMBULANCES). Further, for each MCD incident location, we calculate the minimum distance between the geographic center of that MCD and (a) the closest hospital (MIN HOSPITAL DISTANCE) and (a) the closest hospital with a cardiac catheritization lab (MIN CCLAB HOSPITAL DISTANCE).[45] Finally, we calculate time-varying incident demographics from the PA EMS dataset including MONTHLY PATIENTS at both the MCD and COUNTY level (a measure of the number of recorded rides in a month in an MCD) and QUARTERLY AMBULANCES, which equals the number of distinct ambulances serving an individual county or MCD in a given quarter.

V. Differences Between Pre-Sample, Within-Sample, and Post-Sample Adoptors

As discussed in Section IV, our estimation strategy evaluates the change in patient health outcome measures in response to the adoption of 911 technology, controlling for observable characteristics as well as the productivity time trend common to all counties within Pennsylvania. To validate this approach, it is important to understand how

[43] Of course, once we use fixed effects at a given level of aggregation in a regression, we can only employ the time-varying incident location demographic variables at that level of aggregation.
[44] For MCD or county characteristics for which data is missing, we use a missing value dummy variable.
[45] We calculate these distances using the addresses in the AHA Hospital Survey for 1994 and 1996.

counties who adopt 911 technology within our sample period differ from those who maintain constant levels of 911 technology within our sample.[46]

Our sample offers several features that enable us to analyze the sources of differences between switching and non-switching counties within our sample. First, the non-switchers in our dataset can be usefully divided into two groups: those who adopt either Basic or E911 technology prior to 1994 (pre-sample adoptors) and those who adopt 911 technology after 1996 (post-sample adoptors).[47] Each of the three groups--within sample adoptors, pre-sample adopters, and post-sample adopters--contains one third of the counties. Second, there are three distinct types of switching behavior: No 911 → Basic 911, No 911 → E911, and Basic 911 → E911.

Table 3 presents county-level average characteristics along several dimensions of potential heterogeneity, dividing the counties into six different "regimes," according to their pre-sample technology and their adoption behavior between 1994 and 1996.[48] First, we compare the population, per capita income, and density of counties according to the switching behavior. Counties who have adopted E911 prior to 1994 tend to have larger populations, per capita incomes, and density.[49] Beyond this distinction, there is no easily discernible pattern among the counties. Indeed, except for the pre-sample adoptors of E911, none of the regime-specific means are significantly different from the remainder of the sample.[50] Figure B illustrates the distribution of county population and per-capita income by regime, showing that except for a small concentration of pre-sample E911 adoptors at the highest ranges, each regime includes counties with a wide range of characteristics. We defer a comparison of the relative health of these different groups

[46] We also analyze the productivity of EMD; however, since we are unable to document a productivity effect from EMD in the context of cardiac emergency health care, we focus here on technology rather than job design in evaluting diffusion and the potential for selectivity. It should be noted, however, that pre-sample EMD adoptors, within-sample EMD adoptors, and post-sample EMD adoptors display similar observable characteristics.

[47] By June, 2000, all but one county in Pennsylavnia has adopted some form of 911 technology.

[48] The means in Table 3 weight each county equally; in contrast, Table 2 weights each *patient* equally, implicitly placing higher overall weight on counties with a greater number of observed emergency incidents. Also see the map in Appendix B for the timing and geographic dispersion of adoption across counties.

[49] For each of these means comparisons, we use the 5% significance level. It is useful to note, however, that both Philadelphia and the near suburbs of Pittsburgh (two of the densest and most populous areas in Pennsylvania) are *post-sample* adoptors. However, we exclude these counties for our analysis (which would have only contributed to the control group) as we believe that the productivity of 911 technology and EMD are likely different in these highly urbanized areas.

[50] It is useful to note, however, that among the switching population, the No 911 → Basic group is both less populous and less dense than the other two groups of adoptors.

until Section VI.B.3. To address the potential concern that some pre-sample E911 adoptors are not a valid "control group" for our within-sample adoptors, we verify below that our empirical results are robust to the exclusion of pre-sample E911 adoptors with extreme characteristics.

VI. Empirical Results

Our empirical analysis proceeds in several steps, following the approach outlined in Section III. Tables 4 and 5 present evidence about the productivity of 911 technology and job design for intermediate health status, as measured at ambulance arrival. We then explore several extensions, including the importance of post-adoption learning, the possibility of interaction effects between 911 technology and job design, and the relationship between 911 technology adoption and alternative theories of technological diffusion. Further, we present evidence about the robustness of the results to potential sources of bias and selectivity. Finally, in Table 8, we analyze hospital outcome measures, including short-term mortality and incurred hospital charges. Our main result, robust across alternative empirical specifications, is the existence of a positive relationship between E911 adoption and improved health care outcomes. Counties that adopt E911 (either by itself or in conjunction with EMD) experience a significant improvement in pre-hospital emergency response productivity, in terms of intermediate health status as well as hospital outcomes.

VI.A. The Effects of 911 Technology and Job Design on Health Status

As motivated in Section III.A, we begin our analysis with a single measure of health status at ambulance arrival. Table 4 focuses on LOW RISK BLOOD PRESSURE. In the first column, we report a simple cross-sectional OLS regression that relates the 911 technology and job design variables to this measure; not only is there no statistical relationship between the effects of these variables,[51] but the coefficients are extremely small (and, for E911 and EMD, the point estimates are negative). The second column employs the differences-in-differences strategy: we include a fixed effect for each county in the sample along with an overall productivity time trend (using quarterly dummy variables). We find a large and statistically significant relationship between E911 and

[51] Except where noted, all regressions report Huber-White standard errors; however, the key results are robust to various clustering schemes, including county/month and mcd/month clustering (See Table 7).

LOW RISK BLOOD PRESSURE.[52] Relative to a baseline where just over 10% of the sample experiences a negative outcome (LOW RISK BLOOD PRESSURE = 0), the adoption of E911 decreases this probability to just over 6%. Further, we can reject the hypothesis that E911 offers no incremental productivity benefit over BASIC 911. This finding is strengthened when we incorporate MCD fixed effects in (4-3),[53] and additional patient characteristic and time-varying incident location heterogeneity controls (beyond MCD fixed effects) in (4-4). With the inclusion of these controls, the estimated effect of E911 increases almost 20% and remains at a similar level of statistical significance. At face value, the parameter estimate in (4-4) predicts that the probability of experiencing blood pressure below 90 is cut in half in those counties who adopt E911 during our sample period.

The inclusion of the nearly 2000 MCD fixed effects significantly improves the overall fit; in a specification test, the restriction imposed by the county-level fixed effect model is rejected in favor of models including MCD fixed effects. As well, observe that Table (4-4) includes a variety of controls that may mitigate the role of potentially confounding factors. For example, we control for changes over time in the ambulance infrastructure as well as the overall call volume experienced in the county. We also control for daily weather at the local level, which might otherwise introduce correlation among neighboring localities in a given time period, and could potentially confound the time trend. Except where noted, the remainder of our empirical work on intermediate health status employs the MCD fixed effects specification with the same set of controls.[54]

The results in Table 4 are provocative; however, the LOW RISK BLOOD PRESSURE measure is but one of several raw measures of intermediate health status. Table 5 presents several regressions employing the same specification as in (4-4) but with

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[52] Rather than employing a linear time trend, we estimate eight quarter dummies to allow for nonlinearity in the time trend, perhaps due to the seasonality of health outcomes (and associated variation in emergency response timeliness). It is useful to note, however, that the significance of the E911 coefficient *does not* depend on the inclusion of this time trend in any form. Indeed, excluding the time trend but including county-level or MCD fixed effects increases the size and significance of the coefficients.

[53] Recall that in Pennsylvania, MCDs are entirely contained in counties.

[54] It should be noted that relatively few of the patient characteristics and incident location demographics are separately significant (though they are jointly significant). Notably, MALE is associated with a lower probability of LOW RISK BLOOD PRESSURE and there is a significant negative relationship between the percentage of black residents in a patient's billing zip code and LOW RISK BLOOD PRESSSURE. Interestingly, in contrast to the strong association with E911, other time-varying measures of incident location heterogeneity (such as those related to the volume of ambulance activity as well as rain and snowfall) are neither individually nor jointly significant.

alternative measures of intermediate health status (LOW RISK PULSE, $HINDEX_1$ and $HINDEX_2$). Recall from Section IV.C.1 that $HINDEX_1$ and $HINDEX_2$ are equal to the predicted probability of survival based on regressions of 48-hour survival on the individual health status measures. Similar to (4-4), E911 is associated with a statistically significant and quantitatively important effect on the LOW RISK PULSE dummy. Relative to a .93 baseline probability of LOW RISK PULSE, E911 increases the probability to more than .96.

For both HINDEX measures, the specifications we report use the log-odds ratio as our dependent variable ($LL\,HINDEX_i = \ln(\frac{HINDEX_i}{1-HINDEX_i})$).[55] As in the earlier specifications, E911 is associated with a substantial increase in the expected level of each of the health indices. In terms of the change in the probability of survival as given by our indices, we calculate that E911 is associated with an increase in the predicted survival probability according to $HINDEX_1$ and $HINDEX_2$ of .0051 and .0045, respectively.[56] As well, for all of the specifications in Table 5, both the BASIC and EMD dummies are insignificant. The specifications include the quarterly dummy time trend, time-of-day, incident location, and patient characteristic controls; a joint F-test for each parameter group is included in the lower half of the table.

Because the distributions of both HINDEX measures are concentrated near 1, and are never less than .54, the log-odds specification still results in a skewed distribution. To better understand the role of the functional form assumption, we also explored linear and log-linear specifications. We find that these alternative specifications lead to greater estimated effects of E911: for both indices, we find that E911 increases $HINDEX_i$ by at least .0095, and the coefficients are significant at the 5% level.[57]

[55] By standard arguments, the log-odds transformation ensures that the domain of the dependent variable varies freely between $(-\infty, \infty)$ and that the shape of the underlying health distribution accords with the patterns found in the biostatistics and physiology literatures (Dawson-Sanders and Trapp, 1994).

[56] This tranlates into a 13% and 11% decrease in the .038 baseline rate of *mortality*. Of course, these elasticity calculations are much smaller in terms of the probability of survival and so we attempt to interpret most of our results in terms of their predicted impact on the absolute percentage point change in the probability of survival.

[57] In particular, the estimated coefficients (and associated standard errors) for $HINDEX_1$ are .0095 (.0041) in the linear specification and .0112 (.0050) when $\ln(HINDEX_1)$ is the dependent variable. In the latter case, the estimate translates into an increase in $HINDEX_1$ of .0107. In each case, we reject the hypothesis that BASIC=EN911 at the 1% level. The results for $HINDEX_2$ are very similar.

Finally, we perform the specification test suggested in Section III.C: we estimate a less restrictive model, with separate coefficients for the returns to switching from No 911 to E911 (λ_{20_00}), the returns to switching from Basic 911 to E911 (λ_{20_10}), and the returns to switching from No 911 to Basic 911 (λ_{10_00}). Our point estimates (with standard errors in parentheses) are $\hat{\lambda}_{20\_00}$=.092 (.052), $\hat{\lambda}_{20\_10}$=.138 (.050), and $\hat{\lambda}_{10\_00}$=.057 (.070). Although these estimates suggest that the returns to switching from No 911 to E911 are "too small" relative to the sum of the returns to the other two switches, we cannot reject the hypothesis $\hat{\lambda}_{10\_00} + \hat{\lambda}_{20\_10} = \hat{\lambda}_{20\_00}$, consistent with our assumption that the returns to technology adoption are similar for different counties. Furthermore, although the point estimate of λ_{20_00} should be larger than the one for λ_{20_10}, the difference between the two estimates is not statistically significant.

Before proceeding, we pause briefly to interpret our finding that Basic 911 and EMD do not have measurable effects on intermediate health status. The contrasting findings for Basic 911 and E911 are consistent with the theory that much of the time delay in dispatching emergency services is incurred in establishing a caller's exact location; then, Basic 911 may even slow down dispatch, especially in its early stages when call-takers are not familiar with more distant geographic areas.[58] Our results about EMD are at this stage less conclusive, because the discussion in Section III.C suggests that the benefits of EMD may continue to accrue after ambulance arrival. Below, we examine the role of EMD for other outcomes. However, our results suggest that EMD does not lead to large improvements in timeliness for cardiac emergencies (for example, through improved allocation of paramedics or ALS ambulances).[59]

VI.B. Extensions

VI.B.1 Post-Adoption Learning

In this section, we analyze how the effects of E911 vary with the time before and after a county's adoption date. We are motivated by two concerns. First, as a robustness check, we would like to confirm that the productivity benefit from E911 does not arise

[58] Of course, Basic 911 may bring benefits in other areas of emergency service, for example in applications such as fire and police where there is a greater public goods problem in reporting emergencies.

[59] In our sample of cardiac patients, 75% of ambulances had paramedic attendants, indicating that paramedics may indeed be a scarce resource; however, EMD adoption did not significantly increase the likelihood that a patient received a paramedic. Pennsylvania law required a paramedic to be present for any ALS treatment, such as defibrillation, EKG, or the use of an IV to administer fluid or medication.

from a time trend that begins prior to adoption. Further, we would like to evaluate whether counties improve their performance over time as call-takers and E911 managers master the new technology, and as dispatching becomes more synchronized with the information provided by the location database.

We address these issues in Figure C, where we plot the coefficients from a regression with the same structure as (5-2), but where we include dummy variables for each of the 9 quarters prior to and after the adoption of E911 by a county. We pool together all counties that adopt E911, and we use the non-switching counties as a control group.[60]

Though not definitive (the confidence intervals for each of these parameters are relatively wide), the results are encouraging. The coefficients associated with all of the quarters prior to adoption are below all but the first coefficient associated with productivity after adoption, and there is no discernible trend in the pre-adoption coefficients in the quarters just prior to adoption. As well, there is some evidence for learning; the quarterly coefficients rise in each of the first four quarters after adoption, and the only coefficient below the pre-adoption coefficients is the quarter immediately following adoption. Together, these findings reinforce our initial inference that the adoption of E911 is associated with an increase in cardiac emergency response productivity and that this benefit persists after learning takes place within the adopting 911 center. Further, our results suggest that our estimates in Tables 4 and 5 may underestimate the overall benefits to E911, because counties that adopt relatively late in the sample may not have realized their full productivity gains by the end of 1996.

VI.B.2 911 Technology and Job Design Interaction Effects

Our discussion in Section II highlighted the potential importance of interaction effects between IT and job design: does the adoption of more advanced IT increase the returns to skill-oriented job design? Table 6A addresses this question through the estimation of a model similar to (5-2), but where we include five dummy variables for each of the five separately identified 911 technology/EMD combinations (NO 911*NO EMD is the omitted category). Given that 911 technology has three levels, we can test

[60] Because adoption dates differ across counties, each coefficient in the figure may be estimated from a different group of counties; for example, a county that adopted in June, 1994 will not contribute to the estimates of productivity 3 or more quarters before adoption, while a county that adopted in July, 1996 will not contribute to the estimates of productivity 3 or more quarters after adoption. Finally, because we do not have outcome data for 1995, each of these counties will have a four-quarter gap in the coefficients to which they contribute.

multiple hypotheses about the returns to 911 technology and the nature of the interaction between 911 technology and EMD. First, consistent with our earlier results, the single organizational element found to have a significant impact in isolation is E911 (we reject equality with either NO 911 or BASIC 911). Second, we perform several distinct tests about the nature of the interaction between 911 technology and EMD (depending on whether we choose to focus on complementarity between EMD and (a) None → Basic adoption; (b) None → E911 adoption; (c) Basic → E911 adoption or (d) a joint test of the restrictions implied by each of the above).[61]

In contrast to theories emphasizing complementarity between IT and skill-oriented job design (or theories that focus on the de-skilling aspects of computerization), we cannot reject the hypothesis of no interaction effects between 911 technology and EMD.[62] In other words, while the results concerning the productivity impact of E911 are robust to accounting for interactions with EMD, we can offer no evidence for the presence of either complementarity or substitutability between IT and job design in improving short-term incident location health outcomes. Since many of the benefits of EMD may not yet have been realized when the ambulance arrives (recall Figure A), this result is perhaps not too surprising; yet, similar results obtain when studying in-hospital mortality. Thus, our results suggest that E911 is neither strongly pro-skilling nor de-skilling.

VI.B.3 Nature of E911 Technology Diffusion

A central prediction of many theories of technology diffusion is that the sequence of adoption will reflect declining marginal productivity of adoption (Griliches, 1957; Rogers, 1983). Indeed, it is precisely this insight which often motivates concern that measuring the productivity benefits associated with the adoption may be upward-biased if the estimate reflects the benefits realized by adoptors rather than the average *potential* adoptor in the sample. Although our survey evidence suggests that the perceived health benefits of E911 adoption played little role in determining the precise order of adoption, we still must consider the possibility of selection. One advantage of our application is

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[61] We also conducted the specification test suggested in Section III.C, allowing each different type of switch in 911 system to have a separate coefficient, and testing the restrictions implied by (A2). We cannot reject the hypothesis that the parametric restrictions we imposed are valid, so we maintain them for our analysis of interaction effects. Further, we repeated the analysis using $HINDEX_1$ and $\ln(HINDEX_1)$ as the dependent variable. The results are similar.

62 The absence of interaction effects between 911 technology and EMD is confirmed in variety of specifications and using our alternative incident location health status measures.

that we observe the middle years of a diffusion process, so that even under this theory of selection, the sample we consider should be drawn from the middle of the distribution of returns (of course, we know little about the shape of this distribution). A second advantage is that we can observe the productivity and characteristics of counties that previously adopted and those who have not yet adopted, in addition to the productivity before and after adoption for counties that switch during our sample period. Although this information can not provide definitive answers to questions about selectivity, it can potentially rule out some particularly simple alternative theories.

We begin by estimating a separate conditional mean of $HINDEX_1$ for each of the nine technology "switching regimes" possible for counties in this sample. Specifically, we estimate separate coefficients for each of the three groups of counties maintaining a single technology level throughout the sample (the non-switchers). In addition, for each population of adoptors (None→ Basic, None → E911, and Basic → E911), we estimate a separate productivity coefficient for the pre-adoption and post-adoption phase in the data (leading to an additional six coefficients). To ease interpretation, we use a linear functional form, de-mean all of the control variables, and suppress the constant. Thus, each coefficient can be interpreted as the conditional expectation of $HINDEX_1$ for a patient (with average characteristics) within that specific regime (recall that the overall survival probability is .962).

We report several parametric restriction tests in the bottom half of Table 6B, including (a) the differences between within-sample switchers and the non-switchers with whom they share a technology level before they switch (i.e., do No 911 → E911 adoptors have a different level of productivity than the group of No 911 non-switchers during the period when both have No 911 technology?); (b) the differences between within-sample switchers and the non-switchers with whom they share a technology level after they switch (i.e., do No 911 → E911 adoptors have a different level of productivity than counties who adopt E911 prior to the beginning of the sample period?); and (c) the differences between within-sample switchers during their pre-adoption and post-adoption phase (i.e., what is the difference in productivity for No 911 → E911 adoptors between their No 911 and E911 phases?).

Several results stand out. First, consistent with our earlier productivity results, there is a boost in the survival probability associated with the adoption of E911, whether or not the adopting county maintains a No 911 or Basic 911 technology at the beginning of the sample period. However, while both of these contrasts are significant at the 10% level, only the Basic → E911 contrast is individually significant at the 1% level. Second, though they are not significantly different than each other, the non-switching E911 (who adopted E911 prior to 1994) have a lower predicted survival probability than both No 911 and Basic non-switchers. According to a theory where E911 is associated with at least some returns for the pre-1994 adoptors, this suggests that the population of early adoptors have particularly poor health outcomes. Third, the two groups of within-sample E911 adoptors are estimated to have the *lowest* (over all groups) survival probabilities prior to their adoption of E911. However, rather than simply converging to the mean of the population, both the No 911 → E911 and Basic → E911 counties "leapfrog" over the survival probabilities of all the groups of non-switchers. In other words, while both of these groups of adoptors begin with lower survival probabilities than non-switching counties who share their technology at the beginning of the period (though only one of these contrasts is significant), both are (marginally) significantly better than the non-switching counties who share their technology at then end of the period (the early adoptors of E911).

To represent this diffusion process graphically, we plot the results from a modified version of this regression in Figure D. In particular, we repeat the analysis of Table 6B, except that we group No 911 and Basic into a single category for simplicity; and, we distinguish between counties that adopted E911 in 1991 or before (so that planning for E911 must have begun long before PSETP provided incentives for adoption) and counties that adopted in the 1992-1993 period. The solid triangles in the Figure represent the coefficients on the dummy variables for counties that adopted E911 in the specified time interval, before they adopted E911. The solid diamonds represent the coefficients corresponding to counties that adopted E911 in the specified time interval, after they adopted. For counties that adopt prior to 1994, we only observe health status after adoption; for counties that adopt after 1996, we only observe health status before adoption. The difference between the post-adoption and pre-adoption coefficients for the 1994-1996 adopters is simply our estimate of the effect of E911. Finally, under the assumptions of our fixed-effect model, the benefit to E911 is constant across counties. The outlined points on the figure represent the survival rates that we would attribute to those counties, using our estimate of the benefit to E911.

In interpreting the estimate for the earliest E911 adopters, recall from our discussion in Section IV that this group includes a few counties with particularly poor levels of $HINDEX_1$ that drive down the average. Similarly, the estimate for the latest E911 adopters includes a few of the very smallest counties, who adopted most recently (if at all) and also have unusually good levels of $HINDEX_1$. Our assumption that the returns to E911 are constant across counties are less likely to hold for these unusual counties.

Our findings shed light on the salience of alternative theories about the process of technological diffusion. The adoptors are neither simply associated with poor health status both prior to and after adoption (which suggests a selectivity bias or mean reversion), nor do these counties experience superior productivity both before and after adoption (which would be consistent with a positive correlation between E911 adoption during our sample period and superior health care infrastructure or more efficient 911 managers). Second, nothing in our results is inconsistent with the simple adoption story where early adopters have low levels of productivity, together with high returns. Under that interpretation, our estimates of the welfare effects of E911 would be too small; if early adopters experience higher incremental returns, these returns would accrue to the large fraction (over 50%) of Pennsylvania's population (excluding Philadelphia and Pittsburgh) who had E911 prior to 1994.

Of course, we cannot rule out alternative theories of selectivity that would lead to lower-than-average returns to E911 during 1994-1996. In a final exercise intended to shed light on this issue, we examined how the returns to E911 adoption vary across counties with different characteristics, within the 1994-1996 period. We found no statistically significant effect of demographics such as population. We also explored how the returns vary with the adopting county's level of $HINDEX_1$ at the beginning of the sample. Although the interaction was not statistically significant at the 10% level, the point estimates are inconsistent with the hypothesis that healthier counties have higher returns to adoption.

VI.B.4 Alternative Time Trends, Clustered Standard Errors, and Sample Limitations

Our final set of extensions evaluate the sensitivity of the relationship between health status outcomes measured at the incident scene and the adoption of E911 to the assumptions underlining the differences-in-differences estimation strategy. Table 7 reports our main robustness checks; however, these are a small subset of the avenues we have explored, and so we discuss both the results in Table 7 as well as ancillary (unreported) results which shed further light on the robustness of our findings.

First, in Table 7A, we relax the assumption that all of the different populations in the data experience a common time trend. Heterogeneity in the trend experienced by different populations is particularly important if one is concerned about the potential for selectivity in the population of adoptors (see, e.g., Blundell and MaCurdy, 1999). For example, it may be possible that the population adopting during our sample is simply associated with a higher overall time trend than the full population. To address this concern, we present two specific alternatives. First, in (7A-1), we assign different time trends based on each county's initial technology level. Similar to earlier specifications, we use quarterly dummy variables. In (7A-2), we include time trends (once again in terms of quarterly dummy variables) for "high-density" counties and MCDs. To accomplish this, we separate the sample into counties (and MCDs) with high or low densities (relative to the median density), and the "high-density county" dummy and "high-density MCD" variables are each interacted with each of the quarter dummies. For both of these specifications, the single 911 technology and job design variable which remains significant is E911 (the coefficient also remains similar to earlier estimates). As well, both the initial-technology and density-specific time trends are not significantly different from the baseline time trend. In addition to these specifications, we also explored a variety of other time trends based on the county's final technology level (the converse of (7A-1)), on county and MCD characteristics such as population and per capita income, and using monthly rather than quarterly dummies. In each of these cases, the 911 coefficient remains significant and similar in magnitude while the alternative time trends themselves remain insignificant.

In Table 7B, we further explore the robustness of our results to alternative econometric assumptions. First, we allow for clustering in computing the standard errors. While the richness of our data and the use of fixed effects for each MCD makes it likely that there is a low level of spurious correlation within an MCD for specific time periods (i.e., there are no "contagion" effects in cardiac emergencies, and the use of weather controls reduces the likelihood of correlation of the error due to traffic or environmental conditions), it is still useful to confirm that within-region correlation for specific increments of time does not reduce the magnitude or significance of our earlier results. Therefore, in (7B-1), we report the results from a regression which includes county-level fixed effects and allows for clustering across observations within a quarter and county. The coefficient on E911 remains similar and significant. As well, we explored several alternative clustering schemes, including, among other things, (a) MCD/month level clustering with MCD fixed effects, (b) County/month level clustering with MCD fixed effects, and (c) MCD/quarter level clustering with county-level fixed effects. In each case, the coefficient on E911 remains significant with similar *t*-statistics, and neither the Basic nor EMD coefficient becomes significant.

Finally, in our county-level comparison in Section IV, we found that, on average, counties who adopt E911 prior to our sample tend to either be larger counties or counties with relatively low survival probabilities (both in terms of the HINDEX measures as well as realized mortality rates). We suggested that these patterns may reflect the underlying economics of technological diffusion – counties with particularly unhealthy populations or who have the opportunity to exploit scale economies may tend to adopt earlier. Although the fact that these early adoptors do not switch during our sample frame likely reduces the selectivity bias in our estimation, they may still contribute to the time trend (and potentially other coefficients as well). Accordingly, Table (7B-2) excludes all counties with populations greater than 300,000 (this eliminates 9 counties) and all counties for whom the 48-hour survival rate is below 95% (eliminating another 10 counties). The core E911 result is robust to the exclusion of these counties, as well as to several other variants.

Summarizing, we conclude that our main result relating health status measured at the scene of emergencies to the adoption of IT remains robust even after accounting for the most likely alternative sources of correlation, such as heterogeneity in the time trend across counties, correlation within a county within specific time periods, and potential dependence upon a few large or low-survival probability counties for which the returns to E911 may be particularly high.

VI.C. Mortality, Hospital Inpatient Charges, and Hospital Transfers

Our final empirical exercise examines the effects of technology and EMD on patient outcomes after hospital admission; these outcome measures were described in some detail in Section IV.C.1. As Section III.A suggests, these measures are useful because they can be related to the welfare benefits of the policy variables. However, we reiterate the caveats outlined in Section IV about these outcome measures; in addition to the wellknown difficulties in interpreting the prices charged by hospitals, our outcome measures reflect only the first hospital visit after the ambulance ride.

Consider first Table 8A, which reports results about survival. We modify our specification somewhat from our earlier analysis of intermediate health status, motivated by the fact that hospital outcome measures will include the effects of a patient's in-hospital experience. Because patients in our sample have access to widely different hospitals, this may introduce substantial heterogeneity. To account for this, we include hospital fixed effects in our preferred specifications. This approach may also account for the fact that different hospitals may transfer patients according to different criteria, as discussed in Section IV.C.1. However, our sample size (together with the extremely low probability of short-term mortality) imposes limits on the number of control variables we can include. Table 8A reports results with county-level fixed effects, as well as county and hospital fixed effects. If we include both MCD and hospital fixed effects, the magnitudes of the coefficients remain similar, but the standard errors grow larger. We use a linear probability model; the results are similar with probit estimation.

Although the estimated effects of E911 on survival are less precisely estimated than those for HINDEX, they are similar (indeed, somewhat larger) in magnitude. We find that E911 adoption is associated with an increase of 6 HOUR SURVIVAL rate of .009, from a baseline of .990. While this increase in the survival probability likely impacts those patients with predicted survival probabilities of less than .99 (due to other characteristics), these estimates do suggest that E911 adoption eliminates a substantial portion of the (very short term) mortality risk.

The estimates for 48 HOUR SURVIVAL are similar, though quantitatively larger. Observe further that the baseline mortality rate is higher, and a proportional increase in the standard errors make the results only marginally significant.[63] To interpret these results in light of our earlier findings, recall that $HINDEX_1$ is calculated as the predicted value for 48 HOUR SURVIVAL based on the health status measurements observed at the incident scene. If the adoption of E911 is uncorrelated with factors affecting patient survival after ambulance arrival, the magnitudes of the estimates in Table 8A should be similar to the estimates (scaled in terms of changing survival probabilities) obtained

[63] When hospital fixed effects are included, the p-value drops to .11 (from p = .07). However, the coefficeint magnitudes are fairly robust; inclusion of both MCD and hospital fixed effects does not noticeably change the magnitudes of the estimated coefficients.

earlier. While similar, these (noisy) estimates of the mortality impact are in fact even higher than those associated with the HINDEX variables.[64] Thus, timely ambulance response appears to have lasting effects; for example, our findings are inconsistent with the hypothesis that subsequent medical intervention somehow mitigates the effects of slower ambulance response.

Another potential benefit of improvements in the emergency response system may be a decrease in the need for expensive medical care. Thus, our final analysis examines the impact of the emergency response system on the realized TOTAL CHARGES of patients. The results are dramatic. The adoption of either BASIC or E911 is associated with approximately a 15% reduction in average total charges on a per patient basis (the average charges are just under $14,000). Moreover, if one combines both medium-term mortality and a measure indicating a high level of charges (POOR OUTCOME equals one if the patient dies or exceeds $20,000 in CHARGES), the change in the likelihood of POOR OUTCOME is significant and ranges between .04 and .06.

Finally, consider our findings about the effects of EMD adoption. Although it may not be surprising that EMD has little effect on intermediate health status, our discussion in Section III.A suggests hospital outcome measures might provide better estimates of EMD's benefits. However, we do not find any significant benefit of EMD, and indeed the point estimates for the effect of EMD are negative. Thus, we conclude that the average benefits of EMD adoption for cardiac patients are at best small, especially in comparison to the effects of E911 (of course, EMD is substantially less expensive). In future work, it might be possible to explore the effects of EMD on other patient populations, or to examine other potential benefits of EMD, such as the allocation of ALS ambulances and paramedics according to patient severity or the reduced use of the "lights-and-siren" emergency response.

VI. Implications and Conclusions

The main contribution of this paper is to document that health care outcomes improve following the adoption of E911. However, to interpret these results from the perspective of social welfare, we must compare the costs and benefits of adoption. Several difficulties arise in performing such a comparison. First, and perhaps most

[64] To draw a direct comparison, it may be more useful to consider the results about $HINDEX_1$ derived from a linear specification, where we estimate that E911 is associated with an increase in $HINDEX_1$ of .0095.

importantly, emergency cardiac response is a small portion of the overall volume of calls handled by 911 centers. Within medical emergencies, cardiac emergencies make up less than one-fifth of all emergencies, and, at least in one Pennsylvania county for which statistics are available, ambulance incidents make up 33% of all dispatched calls (just a little over 50% are police and the remainder are associated with fire). Second, while we can relate the benefits for an average-sized county to an average cost system, we do not have the information to estimate the optimal adoption date, because quality is increasing and price is declining over time.

Nonetheless, it still may be useful to compare a rough estimate of adoption costs to an estimate of the benefit of E911 for cardiac emergencies. The average population of Pennsylvania counties is 272,000 and based on industry sources, we estimate that initial adoption costs are approximately $2 million. The technology should last at least five to seven years; furthermore, subsequent upgrades to the technology may be less costly than the initial adoption. E911 also increases operating costs somewhat. Taking all of these factors into account, a rough estimate of the annualized cost is $400,000. Our estimates of the effect of E911 adoption on the 48-hour survival probability range from .005 to .017 (including both our results for intermediate health status as measured by $HINDEX_1$ and the direct effect of E911 on mortality). Since the average number of patients per county in our sample is 129 per year, if we value the patient's improvement in health at $100,000, our estimates of the benefits to E911 range from $64,500 to $219,000. This implies that the benefits to E911 for cardiac patients alone defray a substantial portion of the adoption costs. Taking into account the fact that cardiac emergencies comprise only a small fraction of all 911 calls, it seems likely that E911 adoption increases social welfare for the average county.

In conclusion, we observe that our analysis in this paper highlights a more general issue about productivity measurement in the service sector. In contrast to studies that attempt to evaluate the gains from IT by aggregating across a wide variety of heterogeneous establishments and applications of IT, our approach has been to identify a specific application and to tailor both the measurement of IT and the productivity analysis to fit the application. While such an approach may not be feasible for every application, such estimates provide an alternative perspective both as to the size of the benefits from IT and the types of output measures (e.g., measures specifically responsive to timeliness) which may form the basis for more consistent productivity estimation in the service sector. The development and evaluation of such measures seems a promising area for further research.

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TABLE 1

VARIABLES* & DEFINITIONS

VARIABLE		FULL VARIABLE NAME	DEFINITION	SOURCE
RAW MEASURES OF PATIENT HEALTH STATUS AND PATIENT EXPENDITURES				
BLOOD PRESSURE		Systolic Blood Pressure	Systolic Blood Pressure as measured @ Scene	PA EMS
RESPIRATION		Respiration Rate	Respiration Rate as measured @ Scene	PA EMS
PULSE		Pulse Rate	Pulse Rate as measured @ Scene	PA EMS
GLASGOW		Glasgow Coma Score	A score from 3-15 indicating how alert and responsive the patient is, where higher scores indicate greater alertness	PA EMS
48 HR SURVIVAL		48 Hour Survival Dummy	Hospital Length of Stay >48 hours *or* Hospital Length of Stay<48 hours and Discharged Alive	PA EMS
6 HR SURVIVAL		6 Hour Survival Dummy	Hospital Length of Stay>6 hours *or* Hospital Length of Stay<6 hours and Discharged Alive	PA EMS
TOTAL CHARGES		Total Charges	Total Hospital Charges	PA EMS
CONSTRUCTED PATIENT HEALTH STATUS MEASURES				
LOW RISK BP		Stable Blood Pressure Dummy	LOW RISK BP = 1 if BLOOD PRESSURE > 90	Authors' Calculation
LOW RISK PULSE		Stable Pulse Rate Dummy	LOW RISK PULSE = 1 if PULSE >= 40	Authors' Calculation
HINDEX1		Health Index 1	Fitted Value from Regression of 48 HR SURVIVAL on (appropriately scaled) BLOOD PRESSSURE, RESPIRATION, PULSE, and GLASGOW (see Appendix A)	Authors' Calculation
HINDEX2		Health Index 2	Fitted Value from Regression of 48 HOUR SURVIVAL on Revised Trauma Score categories (see Appendix A)	Authors' Calculation
POOR OUTCOME		Poor Outcome Dummy	POOR OUTCOME = 1 if Incident Results in Death *or* Total Charges > $20000 *or* Discharge from Hospital to Hospital	PA EMS
COUNTY-LEVEL EMERGENCY RESPONSE SYTEM MEASURES				
NO 911		No 911 Dummy	"No 911" in County on INCIDENT DATE	MIT PSAP Survey
BASIC 911		Basic 911 Dummy	"Basic 911" in County on INCIDENT DATE	MIT PSAP Survey
E911		Enhanced 911 Dummy	"Enhanced 911" in County on INCIDENT DATE	MIT PSAP Survey
EMD		Emergency Dispatch System Dummy	Emergency Dispatch System in County on INCIDENT DATE	MIT PSAP Survey
INCIDENT DATE				
INCIDENT DATE		Date of Incident		PA EMS
QUARTER DUMMIES		Quarterly Dummies	Eight Quarterly Dummies Corresponding to the Quarter of the INCIDENT DATE	PA EMS
NON-HEALTH STATUS PATIENT CHARACTERISTICS				
MALE		Male Sex Dummy	Male Sex Dummy	PA EMS
AGE		Patient Age	Patient Age on INCIDENT DATE	PA EMS
HOUR DUMMIES		Incident Time-of-Day Dummies	Dummies for Incident Time-of-Day	PA EMS
MEDICARE		Medicare Dummy	MEDICARE = 1 if Primary Insurance is Medicare	PA EMS
MEDICAID		Medicaid Dummy	MEDICAID = 1 if Primary Insurance is Medicaid	PA EMS
PRIVATE		Private Health Insurance Dummy	PRIVATE = 1 if Primary Insurance is Blue Cross, Private HMO, or Other Private Health Insurance	PA EMS
SELF_PAY		Self-Pay Dummy	SELF_PAY = 1 if No Insurance	PA EMS
PATIENT LOCATION DEMOGRAPHICS				
PATIENT BILLING ADDRESS ZIP CODE DEMOGRAPHICS (Z_*)				
ZIP	PERCAP INCOME	Per Capita Income	Per Capita Income (1990 Census)	US Census Bureau Zip Code Gazetteer
ZIP	% BLACK	Percentage Black in Population	Percentage Black In Zip Code Population (1990 Census)	US Census Bureau Zip Code Gazetteer
ZIP	% FOREIGN	Percentage Foreign-Born	Percentage Foreign-Born in Population (1990 Census)	US Census Bureau Zip Code Gazetteer
ZIP	% High School or Better	Percentage Completed High School Education or Better	Percentage Completed High School Education or Better (1990 Census)	US Census Bureau Zip Code Gazetteer
PATIENT INCIDENT LOCATION DEMOGRAPHICS – MCD-LEVEL (M_*)				
M	POPULATION	MCD Population	MCD Population (1990 Census)	US Census Bureau MCD Gazetteer
M	DENSITY	MCD Population Density	POPULATION / MCD SQUARE MILES (1990 Census)	US Census Bureau MCD Gazetteer
M	PERCAP INCOME	Per Capita Income	Per Capita Income (1990 Census)	US Census Bureau MCD Gazetteer

PATIENT INCIDENT PRE-HOSPITAL INFRASTRUCTURE – MCD-LEVEL (M_*)				
M	TOTAL PATIENTS	Total Emergency Patients in MCD (1994-1996)	Total Emergency Patients in MCD (1994-1996)	PA EMS
M	MONTHLY PATIENTS	Total Emergency Patients in MCD in INCIDENT Month	Total Emergency Patients in MCD in INCIDENT Month	PA EMS
M	TOTAL # AMBULANCES	Total Distinct Ambulances in MCD (1994-1996)	Total Distinct Ambulances in MCD (1994-1996)	PA EMS
M	QUARTERLY AMBULANCES	Total Distinct Ambulances in INCIDENT Quarter	Total Distinct Ambulances in INCIDENT Quarter	PA EMS
M	QUARTERLY. ALS AMBULANCES	Total Distinct ALS Ambulances in INCIDENT Quarter	Total Distinct ALS Ambulances in INCIDENT Quarter	PA EMS
M	PRECIPITATION	Daily Precipitation	PRECIPITATION = 1 if Precipitation on INCIDENT DATE > 2 inches	Natl Climatic Data Ctr
M	SNOWFALL	Daily Snowfall	SNOWFALL = 1 if Snowfall on INCIDENT DATE > 4 inches	Natl Climatic Data Ctr
M	SNOW DEPTH	Snow Depth	SNOW DEPTH = 1 if Snow Depth on INCIDENT DATE > 12 inches	Natl Climatic Data Ctr
M	MAX TEMP	Daily Maximum Temperature	MAX TEMP= 1 if Maximum Temperature Reading on INCIDENT DATE > 90 F	Natl Climatic Data Ctr
M	MIN TEMP	Daily Minimum Temperature	MIN TEMP =1 if Minimum Temperature Reading on INCIDENT DATE < 0 F	Natl Climatic Data Ctr
PATIENT INCIDENT LOCATION DEMOGRAPHICS – COUNTY-LEVEL (C_*)				
C	POPULATION	County Population	County Population (1990 Census)	US Census Bureau
C	DENSITY	County Population Density	C_POPULATION / C_SQUARE MILES (1990 Census)	US Census Bureau
C	PERCAP INCOME	Per Capita Income	County Per Capita Income (1990 Census)	US Census Bureau
C	MONTHLY PATIENTS	Total Emergency Patients in County in Given Month	Total Emergency Patients in County in Given Month	PA EMS
C	TOTAL HOSPITALS	Total Distinct Hospitals in County	Total Distinct Hospitals in County	AHA Survey

* The natural logarithm of a variable, X, is denoted L X. The log-odds ratio of a variable, X, is denoted LL X

TABLE 2
SUMMARY STATISTICS

VARIABLE	N	MEAN	STANDARD DEVIATION
RAW MEASURES OF PATIENT HEALTH STATUS AND PATIENT EXPENDITURES			
BLOOD PRESSURE	16725	137.107	49.612
RESPIRATION	16725	21.466	8.112
PULSE	16725	86.085	35.255
GLASGOW	16725	14.133	2.923
48 HR SURVIVAL	16725	0.962	0.192
6 HR SURVIVAL	16725	0.990	0.100
TOTAL CHARGES	16725	13991.66	17699.13
CONSTRUCTED PATIENT HEALTH STATUS MEASURES			
LOW RISK BP	16725	0.896	0.305
LOW RISK PULSE	16725	0.934	0.248
POOR OUTCOME	16725	0.250	0.433
COUNTY-LEVEL EMERGENCY RESPONSE SYTEM MEASURES			
NO 911	16725	0.148	0.355
BASIC 911	16725	0.172	0.377
E911	16725	0.680	0.466
EMD	16725	0.497	0.500
NON-HEALTH STATUS PATIENT CHARACTERISTICS			
MALE	16725	0.516	0.500
AGE	16725	70.309	12.860
MEDICARE	16725	0.678	0.467
MEDICAID	16725	0.046	0.209
PRIVATE	16725	0.207	0.405
SELF_PAY	16725	0.009	0.093
PATIENT LOCATION DEMOGRAPHICS			
PATIENT BILLING ADDRESS ZIP CODE DEMOGRAPHICS (Z_*)			
ZIP PERCAP INCOME	14944	13643.11	4600.691
ZIP % BLACK	14944	0.040	0.102
ZIP % FOREIGN	14944	0.024	0.022
ZIP % High School or Better	14944	0.177	0.042
PATIENT INCIDENT LOCATION DEMOGRAPHICS – MCD-LEVEL (M_*)			
M POPULATION	12943	13596.54	21798.24
M DENSITY	12943	945.372	943.693
M PERCAP INCOME	7855	11758.12	2613.094
PATIENT INCIDENT PRE-HOSPITAL INFRASTRUCTURE – MCD-LEVEL (M_*)			
M TOTAL PATIENTS	16725	515.850	818.627
M MONTHLY PATIENTS	16725		
M TOTAL # AMBULANCES	16725	11.434	10.516
M QUARTERLY AMBULANCES	16725	8.026	7.188
M QUART. ALS AMBULANCES	16725	5.975	5.823
M PRECIPITATION > 2 INCHES	16725	0.006	0.078
M SNOWFALL > 4 INCHES	16725	0.016	0.126
M SNOW DEPTH > 12 INCHES	16725	0.069	0.254
M MAX. TEMPERATURE > 90	16725	0.020	0.139
M MIN. TEMPERATURE < 0	16725	0.027	0.163
PATIENT INCIDENT LOCATION DEMOGRAPHICS – COUNTY-LEVEL (C_*)			
C POPULATION	16725	272282.000	191362.400
C DENSITY	16725	563.663	687.654
C PERCAP INCOME	16725	18211.830	4042.793
C MONTHLY PATIENTS	16725	58.906	51.537
C TOTAL HOSPITALS	16725	3.592	2.162

TABLE 3
PATTERNS OF SWITCHING BEHAVIOR

	REGIME					
	No 911 Non-switcher	**Basic 911 Non-switcher**	**E911 Non-switcher**	**None to Basic Switcher**	**None to E911 Switcher**	**Basic to E911 Switcher**
# COUNTIES	5	6	23	8	9	14
AVERAGE COUNTY CHARACTERISTICS BY REGIME						
COUNTY POPULATION	128983.20	68393.83	225834.20	53841.13	92705.33	113849.60
CNTY PER CAPITA INCOME	14881.40	15563.83	17596.57	16474.50	14966.11	15521.57
COUNTY DENSITY	227.80	99.17	464.13	74.63	148.78	172.57
PATIENT AGE	68.81	69.16	70.25	68.61	70.85	69.79
48 HR SURVIVAL	0.968	0.971	0.951	0.975	0.967	0.974

TABLE 4
IMPACT OF EMS VARIABLES ON HEALTH STATUS

	Dependent Variable = LOW RISK BLOOD PRESSURE											
	(4-1) Emergency Medical System (EMS) Variables Only			**(4-2)** EMS Variables and Quarterly Dummies (County FE)			**(4-3)** EMS Variables and Quarterly Dummies (MCD FE)			**(4-4)** EMS Variables with Patient & Time Controls (MCD FE)		
EMERGENCY RESPONSE SYSTEM VARIABLES												
BASIC	0.001 (0.008)			0.005 (0.015)			0.003 (0.017)			0.004 (0.017)		
E911	-0.009 (0.007)			**0.040 (0.016)**			**0.047 (0.018)**			**0.049 (0.018)**		
EMD	-0.006 (0.005)			-0.012 (0.011)			-0.017 (0.012)			-0.015 (0.012)		
PARAMETRIC RESTRICTIONS	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restri ct	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	1	2.26	0.133	**1**	**5.99**	**0.014**	**1**	**7.87**	**0.005**	**1**	**8.61**	**0.003**
QUARTERLY DUMMIES												
1994Q2				-0.006 (0.008)			-0.007 (0.009)			-0.013 (0.010)		
1994Q3				-0.005 (0.009)			-0.013 (0.010)			-0.016 (0.011)		
1994Q4				-0.006 (0.009)			-0.010 (0.010)			-0.016 (0.011)		
1996Q1				0.000 (0.009)			-0.002 (0.010)			-0.009 (0.010)		
1996Q2				-0.015 (0.010)			-0.015 (0.010)			-0.022 (0.011)		
1996Q3				-0.004 (0.010)			-0.007 (0.011)			-0.016 (0.012)		
1996Q4				**-0.025 (0.011)**			**-0.026 (0.012)**			**-0.032 (0.013)**		
PATIENT CHARACTERISTICS												
MALE										**-0.027 (0.005)**		
AGE 46-55										0.024 (0.014)		
AGE 56-65										-0.022 (0.014)		
AGE 66-75										-0.022 (0.015)		
AGE 75+										-0.002 (0.015)		
MEDICAID										-0.005 (0.014)		
PRIVATE										-0.016 (0.009)		
SELF-PAY										-0.054 (0.031)		
OTHER INSURANCE										0.004 (0.012)		
INCIDENT TIME-OF-DAY CATEGORY										**Significant**		

PATIENT BILLING ADDRESS ZIP CODE CHARACTERISTICS				
Z_BLACK				**-0.161 (0.045)**
Z_FOREIGN				0.045 (0.208)
Z_L(PERCAP INCOME)				-0.028 (0.023)
Z_%HIGH SCHOOL+				0.058 0.137
TIME-VARYING INCIDENT LOCATION CHARACTERISTICS				
MCD LEVEL				
M_QUARTERLY AMBULANCES				-0.002 (0.002)
M_QUARTERLY ALS AMBULANCES				0.001 (0.003)
SNOWFALL > 4 INCHES				-0.006 (0.022)
SNOW DEPTH > 12 INCHES				-0.002 (0.011)
PRECIPITATION > 2 INCHES				0.024 (0.029)
MAX TEMP > 90 F				-0.034 (0.020)
MIN TEMP < 0 F				-0.021 (0.017)
COUNTY LEVEL				
C_L(MONTHLY PATIENTS)				0.009 (0.008)
Constant	**.905 (0.006)**	**0.881 (0.012)**	**0.881 (0.013)**	**0.840 (0.229)**
R-Squared	0.0004	0.0180	0.1415	0.1546
Observations	16725	16725	16725	16725

TABLE 5
IMPACT OF EMS VARIABLES ON HEALTH STATUS: ALTERNATIVE HEALTH STATUS MEASURES

	(5-1) EMS Variables with Patient & Time Controls (MCD FE)			**(5-2)** EMS Variables with Patient & Time Controls (MCD FE)			**(5-3)** EMS Variables with Patient & Time Controls (MCD FE)		
DEPENDENT VAR.	LOW RISK PULSE			LL HINDEX1			LL HINDEX2		
EMERGENCY RESPONSE SYSTEM VARIABLES									
BASIC	0.005 (0.014)			0.008 (0.050)			-0.005 (0.048)		
EN911	**0.035 (0.015)**			**0.133 (0.051)**			**0.119 (0.048)**		
EMD	-0.010 (0.010)			-0.033 (0.034)			-0.029 (0.032)		
PARAMETRIC RESTRICTIONS	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	**1**	**5.08**	**0.024**	**1**	**7.64**	**0.006**	**1**	**8.60**	**0.003**
NONE → BASIC + BASIC → E911 = NONE → E911									
CONTROL VARIABLES									
# of Obs - # of Parameters = 14557	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
QUARTERLY DUMMIES	7	1.55	0.144	7	1.11	0.354	7	0.99	0.434
INCIDENT TIME-OF-DAY DUMMIES	**8**	**11.64**	**0.000**	**8**	**9.53**	**0.000**	**8**	**10.20**	**0.000**
PATIENT CHARACTERISTICS	**14**	**5.44**	**0.000**	**14**	**5.76**	**0.000**	**14**	**5.51**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	8	0.60	0.782	8	0.81	0.597	8	0.66	0.728
R-Squared	0.1691			0.1661			0.1636		
Adjusted R-Squared	0.0582			0.0548			0.0520		
Observations	16725			16725			16725		

TABLE 6A
IMPACT OF EMS VARIABLES ON HEALTH STATUS: INTERACTION EFFECTS

	Dependent Variable = LL HINDEX1		
	EMS Interactions Including Patient and Incident Location Characteristics (MCD FE)		
EMERGENCY RESPONSE SYSTEM VARIABLES			
BASIC* NO EMD	0.025 (0.058)		
E911* NO EMD	**0.152** **(0.059)**		
NO 911* EMD	0.025 (0.086)		
BASIC*EMD	-0.016 (0.089)		
E911* EMD	**0.113** **(0.057)**		
911 PARAMETRIC RESTRICTIONS	#Restrict	F-stat	p-value
PRACTICE TESTS			
NO 911 = BASIC	2	0.21	0.814
NO 911 = E911	**2**	**3.50**	**0.030**
BASIC = E911	**2**	**3.94**	**0.020**
EMD = NO EMD	3	0.47	0.702
INTERACTION TESTS			
EMD*BASIC – EMD*NO911 – NOEMD*BASIC = 0	1	0.39	0.532
EMD*E911 – NOEMD*E911 – EMD*NO911 = 0	1	0.48	0.487
(EMD*E911 + NOEMD*BASIC) – NOEMD*E911 – EMD*BASIC = 0	1	0.00	0.970
JOINT TEST OF PREVIOUS THREE	2	0.28	0.759
CONTROL VARIABLES			
QUARTERLY DUMMIES	7	1.11	0.352
INCIDENT TIME-OF-DAY DUMMIES	**8**	**9.50**	**0.000**
PATIENT CHARACTERISTICS	**14**	**5.75**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	8	0.80	0.603
R-Squared	0.1661		
Adjusted R-Squared	0.0547		
Observations	16725		

TABLE 6B
IMPACT OF EMS VARIABLES ON HEALTH STATUS: TECHNOLOGY REGIMES

	Dependent Variable =HINDEX1		
	EMS Regime Variables with Patient and Time Controls		
EMS REGIME VARIABLES			
NO 911, NON-SWITCHER	**0.964** **(0.003)**		
BASIC, NON-SWITCHER	**0.964** **(0.003)**		
E911, NON-SWITCHER	**0.961** **(0.002)**		
NO 911 → BASIC SWITCHER, NO 911 PHASE	**0.966** **(0.004)**		
NO 911 → BASIC SWITCHER, BASIC PHASE	**0.966** **(0.004)**		
NO 911 → E911 SWITCHER, NO 911 PHASE	**0.959** **(0.003)**		
NO 911 → E911 SWITCHER, E911 PHASE	**0.965** **(0.003)**		
BASIC → E911 SWITCHER, BASIC PHASE	**0.958** **(0.003)**		
BASIC → E911 SWITCHER, E911 PHASE	**0.967** **(0.003)**		
911 PARAMETRIC RESTRICTIONS			
# of Obs - # of Parameters=16679	# Restrict	F-stat	p-value
NO 911, NON-SWITCHER = NO 911 → BASIC SWITCHER, NO 911 PHASE	1	0.33	0.565
NO 911, NON-SWITCHER = NO 911 → E911 SWITCHER, NO 911 PHASE	1	2.00	0.158
BASIC, NON-SWITCHER = BASIC → E911 SWITCHER, BASIC PHASE	**1**	**4.05**	**0.044**
BASIC, NON-SWITCHER = NO 911 → BASIC SWITCHER, BASIC PHASE	1	0.17	0.676
E911, NON-SWITCHER = NO 911 → E911 SWITCHER, NO 911 PHASE	1	2.36	0.124
E911, NON-SWITCHER = BASIC → E911 SWITCHER, E911 PHASE	**1**	**4.92**	**0.027**
NO 911 → BASIC SWITCHER, NO 911 PHASE = NO 911 → BASIC SWITCHER, BASIC PHASE	1	0.00	0.960
NO 911 → E911 SWITCHER, NO 911 PHASE = NO 911 → E911 SWITCHER, E911 PHASE	*1*	*2.83*	*0.093*
BASIC → E911 SWITCHER, BASIC PHASE = BASIC → E911 SWITCHER, E911 PHASE	**1**	**7.59**	**0.006**
CONTROL VARIABLES			
QUARTERLY DUMMIES	7	1.68	0.110
INCIDENT TIME-OF-DAY DUMMIES	**8**	**13.46**	**0.000**
PATIENT CHARACTERISTICS	**14**	**7.26**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	**8**	**2.67**	**0.006**
R-Squared	0.9949		
Observations	16725		

TABLE 7A
TIME TRENDS

	Dependent Variable = LL HEALTH INDEX 1					
	(7A-1) (5-2) Including Technology-Specific Time Trend (MCD FE)			**(7A-2)** (5-2) Including MCD and County Characteristic Trends (MCD FE)		
EMERGENCY RESPONSE SYSTEM VARIABLES						
BASIC	0.008 (0.065)			0.007 (0.051)		
EN911	**0.124 (0.063)**			**0.125 (0.054)**		
EMD	-0.033 (0.035)			-0.047 (0.037)		
PARAMETRIC RESTRICTIONS	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = EN911	**1**	**4.81**	**0.028**	**1**	**6.70**	**0.010**
CONTROL VARIABLES						
# of Obs - # of Parameters	14738			14741		
	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
QUARTERLY DUMMIES	7	0.82	0.571	7	0.81	0.575
HIGH-DENSITY COUNTY DUMMY* QUARTERLY DUMMIES				7	0.79	0.594
HIGH-DENSITY MCD DUMMY* QUARTERLY DUMMIES				7	0.41	0.896
INITIAL TECHNOLOGY DUMMY* QUARTERLY DUMMIES	*24*	*1.43*	*0.080*			
INCIDENT TIME-OF-DAY DUMMIES	**8**	**9.34**	**0.000**	**8**	**9.51**	**0.000**
PATIENT CHARACTERISTICS	**14**	**5.72**	**0.000**	**14**	**5.70**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	8	0.76	0.642	8	0.71	0.679
R-Squared	0.1676			0.1666		
Adjusted R-Squared	0.0554			0.0545		
Observations	16725			16725		

TABLE 7B
CLUSTERING AND SAMPLE SELECTION

	Dependent Variable = LL HINDEX 1					
	(7B-1) EMS Variables with Patient & Time Controls and Clustered Standard Errors (by Fips and quarter) (Fips FE)			**(7B-2)** (5-2) Excluding Large and Low Health Counties (MCD FE)		
EMERGENCY RESPONSE SYSTEM VARIABLES						
BASIC	0.013 (0.048)			-0.026 (0.053)		
E911	**0.112** **(0.044)**			**0.118** **(0.053)**		
EMD	-0.024 (0.030)			-.016 (0.038)		
PARAMETRIC RESTRICTIONS	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = EN911	**1**	**6.57**	**0.010**	**1**	**8.45**	**0.004**
CONTROL VARIABLES						
# of Obs - # of Parameters	16612			10017		
	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
QUARTERLY DUMMIES	7	1.63	0.122	7	1.26	0.264
INCIDENT TIME-OF-DAY DUMMIES	**8**	**10.03**	**0.000**	**8**	**5.85**	**0.000**
PATIENT CHARACTERISTICS	**14**	**6.77**	**0.000**	**14**	**5.25**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS	**16**	**2.00**	**0.010**	8	1.50	0.150
R-Squared	0.0362			0.1634		
Adjusted R-Squared	0.0297			0.0417		
Observations	16725			11476		

TABLE 8A
SURVIVAL REGRESSIONS

	(8A-1) EMS Variables with Patient & Time Controls (Fips FE)			**(8A-2)** EMS Variables with Patient & Time Controls (Fips & Hospital FE)			**(8A-3)** EMS Variables with Patient & Time Controls (Fips FE)			**(8A-4)** EMS Variables with Patient & Time Controls (Fips & Hospital FE)		
DEPENDENT VARIABLE	6 HOUR SURVIVAL			6 HOUR SURVIVAL			48 HOUR SURVIVAL			48 SURVIVAL		
EMERGENCY SYSTEMS VARIABLES												
BASIC	0.001 (0.005)			0.001 (0.005)			0.006 (0.009)			0.005 (0.009)		
E911	*0.010* *(0.005)*			*0.009* *(0.005)*			*0.017* *(0.010)*			0.016 (0.010)		
EMD	-0.003 (0.004)			-0.002 (0.004)			-0.010 (0.007)			-0.007 (0.007)		
911 PARAMETRIC RESTRICTIONS												
# of Obs - # of Parameters	16612			16419			16612			16419		
	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	**1**	**5.59**	**0.018**	**1**	**4.48**	**0.034**	1	2.44	0.118	1	1.91	0.167
CONTROL VARIABLES												
QUARTERLY DUMMIES	*7*	*1.75*	*0.092*	7	1.54	0.148	**7**	**2.08**	**0.042**	**7**	**2.40**	**0.019**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**2.08**	**0.034**	**8**	**2.48**	**0.011**	**8**	**2.42**	**0.013**	**8**	**2.87**	**0.003**
PATIENT CHARACTERISTICS	14	1.22	0.251	14	1.50	0.102	**14**	**6.07**	**0.000**	**14**	**6.05**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	**16**	**1.88**	**0.018**	**16**	**1.67**	**0.045**	16	1.34	0.160	16	1.46	0.106
R-Squared	0.0075			0.0247			0.0148			0.0302		
Adjusted R-Squared	0.0008			0.0066			0.0082			0.0122		
Observations	16725			16725			16725			16725		

TABLE 8B
OVERALL DOWNSTREAM IMPACTS

	(8B-1) EMS Variables with Patient & Time Controls (County and Hospital FE)			(8B-2) EMS Variables with Patient & Time Controls (County FE)			(8B-3) EMS Variables with Patient & Time Controls (County and Hospital FE)		
DEPENDENT VARIABLE	LN(TOTAL CHARGES)			POOR OUTCOME			POOR OUTCOME		
EMERGENCY SYSTEMS VARIABLES									
BASIC	**-0.161** **(0.037)**			-0.021 (0.019)			**-0.046** **(0.017)**		
E911	**-0.147** **(0.040)**			**-0.043** **(0.020)**			**-0.064** **(0.019)**		
EMD	-0.035 (0.027)			-0.018 (0.014)			-0.020 (0.014)		
911 PARAMETRIC RESTRICTIONS									
# of Obs - # of Parameters	16419			16612			16419		
	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	1	0.18	0.671	1	1.71	0.191	1	1.15	0.283
CONTROL VARIABLES									
QUARTERLY DUMMIES	**7**	**51.39**	**0.000**	**7**	**21.99**	**0.000**	**7**	**16.85**	**0.000**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**4.83**	**0.000**	**8**	**3.46**	**0.001**	**8**	**3.55**	**0.000**
PATIENT CHARACTERISTICS	**14**	**5.35**	**0.000**	**14**	**6.91**	**0.000**	**14**	**3.92**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	**16**	**2.59**	**0.001**	**16**	**5.56**	**0.00**	16	1.30	0.186
R-Squared	0.2907			0.0717			0.1571		
Adjusted R-Squared	0.2775			0.0655			0.1415		
Observations	16725			16725			16725		

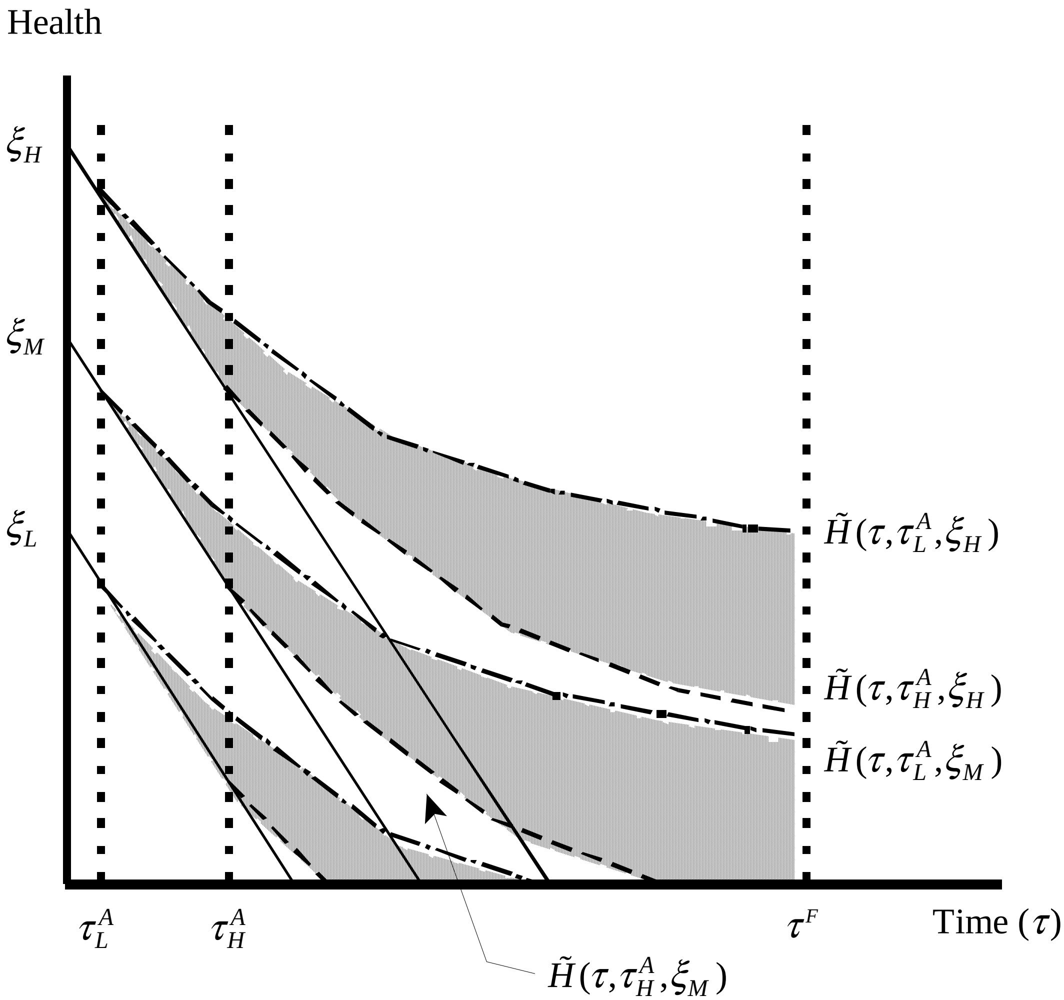
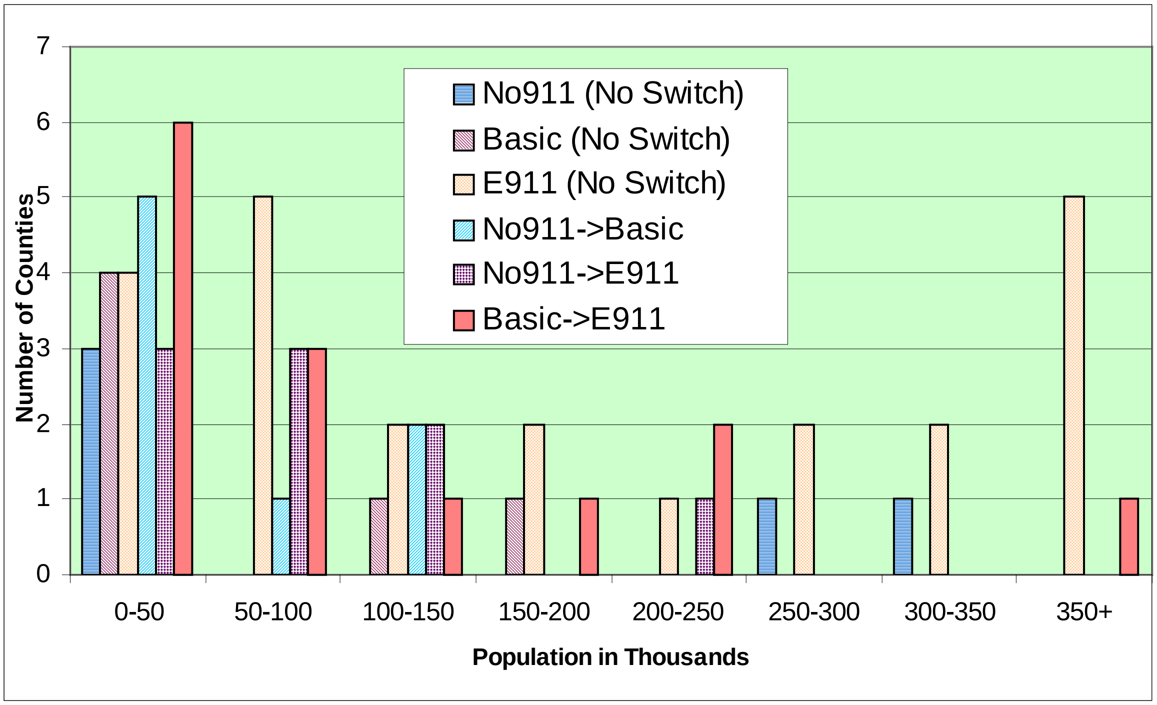
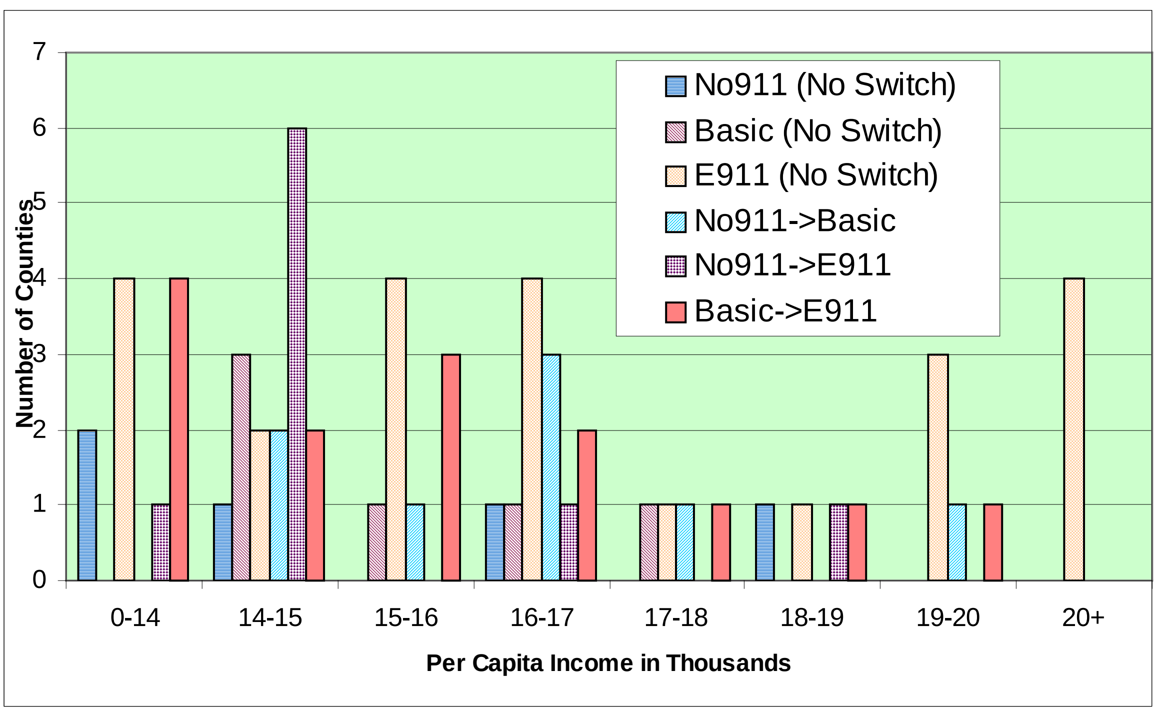
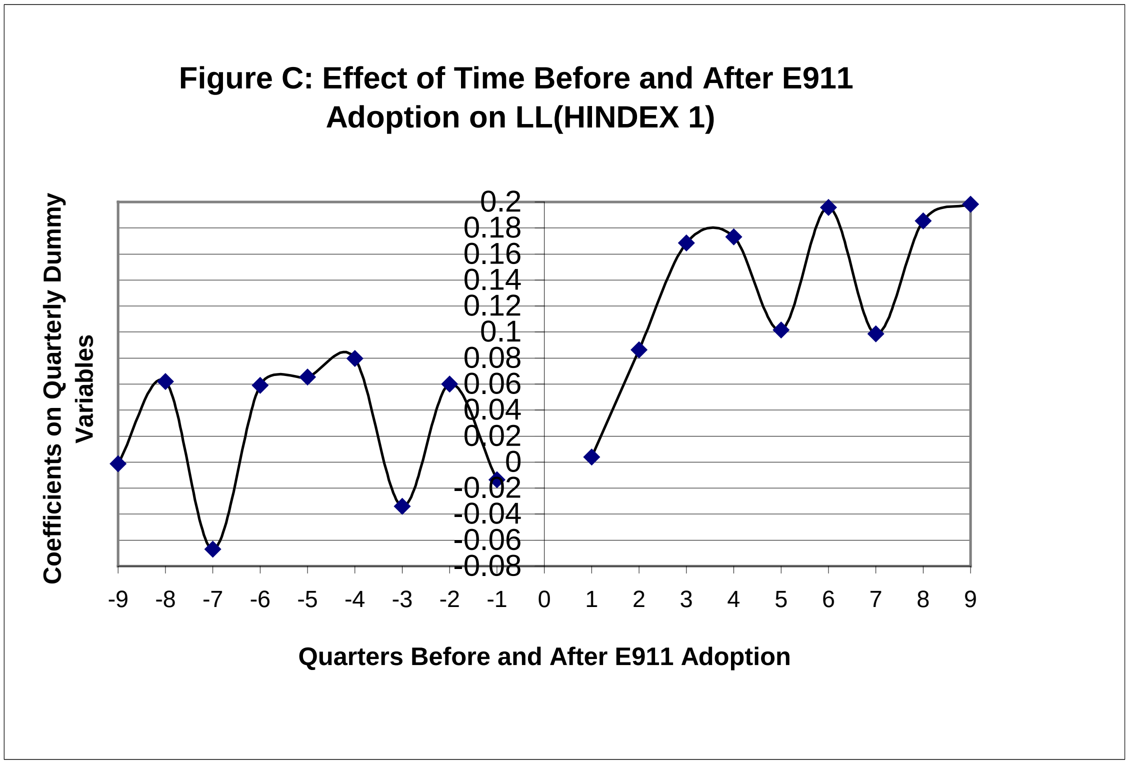


Figure A: The Health Status Production Function

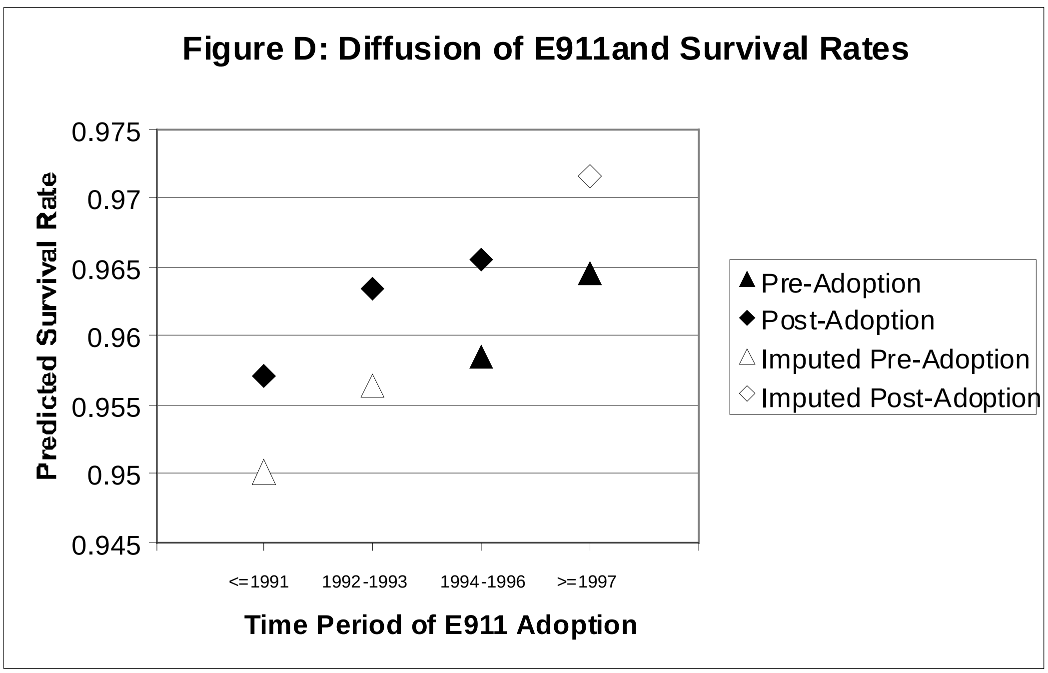
Figure B: Histograms of County Demographics by 911 System Switching Regimes







Notes: The coefficients are derived from a regression of LL(HINDEX1) on dummy variables for the quarters before and after adoption, as well as the control variables used in Table 5.



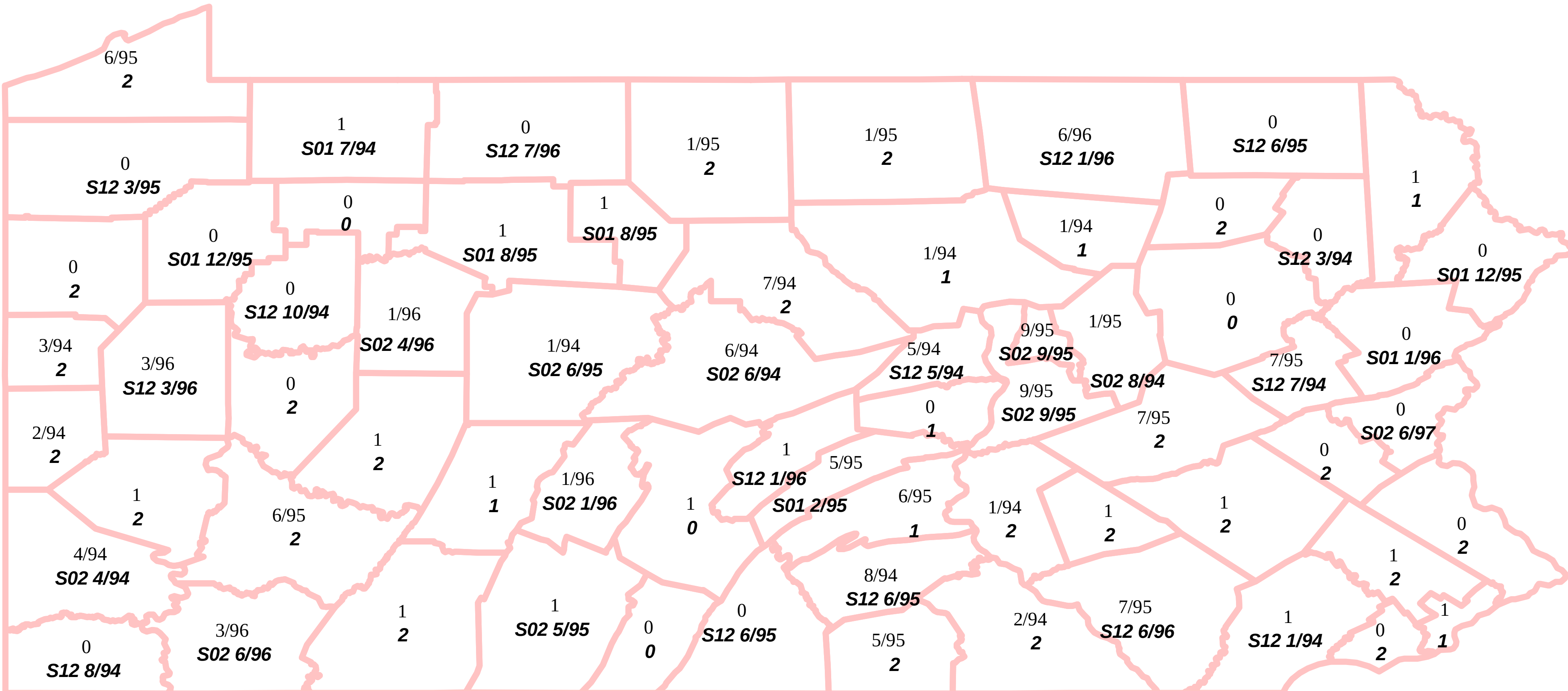
Notes: The points on the figure represent the coefficients on dummy variables for each group of counties in a regression that is the same as the one reported in Table 6B, except that No 911 and Basic are pooled into a single category, and further we distinguish between counties that adopted E911 in 1991 or earlier, and counties that adopted E911 in 1992-1993.

APPENDIX A
HEALTH INDEX PROBIT EQUATION

Dependent Variable = 48 HOUR SURVIVAL		
	HINDEX 1	**HINDEX 2**
GLASGOW SCORE		
CAT1 (4<=Glasgow<=5)	0.010 (0.011)	
CAT2 (6<=Glasgow<=8)	0.008 (0.008)	
CAT3 (9<=Glasgow<=12)	*0.014* *(0.005)*	
CAT4 (13<=Glasgow<=15)	**0.089** **(0.026)**	
RESPIRATION		
CAT1 (1<=Resp<=5)	-0.030 (0.030)	
CAT2 (6<=Resp<=9)	0.013 (0.008)	
CAT3 (30<=Resp)	**-0.038** **(0.020)**	
CAT4 (10<=Resp<=29)	-0.011 (0.007)	
BLOOD PRESSURE		
CAT1 (1<=Systol<=49)	-0.006 (0.033)	
CAT2 (50<=Systol<=75)	-0.001 (0.009)	
CAT3 (76<=Systol<=89)	0.002 (0.008)	
CAT4 (>=90)	**0.084** **(0.020)**	
LOW RISK PULSE		
LOW RISK PULSE (Pulse>=40)	**0.020** **(0.010)**	
REVISED TRAUMA SCORE		
CAT1 (3<=RTS<4)		*0.013* *(0.005)*
CAT2 (4<=RTS<5)		**0.018** **(0.002)**
CAT3 (5<=RTS<6)		**0.022** **(0.002)**
CAT4 (6<=RTS<7)		**0.022** **(0.001)**
CAT5 (7<=RTS<8)		**0.274** **(0.014)**
Pseudo R-Squared	0.2022	0.1922
# OBS	16725	16725
Log Likelihood	-2166.927	-2193.925

Coefficients are measured as differences in probability.
Revised Trauma Score (RTS) is calculated as *RTS = 0.9368*(Glasgow Coma Scale Points) + 0.7326*(Systolic Blood Pressure Points) + 0.2908*(Respiration Rate Points)*, where points coincide with the category numbers in the calculation of HINDEX1. Values for the RTS range from 0 to 7.8408. A threshold of RTS < 4 has been proposed to identify patients who should be treated in a trauma center. See www.trauma.org/scores

Appendix B
EMD and 911 Adoption
Pennsylvania Counties, 1994-1996



Legend:

Top Label: EMD System or Switching Date (0=No EMD, 1=EMD)
Bottom Label: 911 System or Switch Type and Date (0=No 911, 1=Basic, 2=E911)

APPENDIX C

MIT 911 Survey

Principal Investigators
Professor Scott Stern, MIT Sloan School & NBER
Professor Susan Athey, MIT & NBER

PART I. CONTACT INFORMATION

Contact Date ______________________________________

County Name ______________________________________

Name of Agency ______________________________________

Telephone # ______________________________________

Contact Name ______________________________________

PART II. EMD Adoption Questions

Definition: EMD = Yes is equivalent to the adoption of a "card-based" system similar to the APCO, Clausen, MPC, or PPC.

1. Do you have a card-based emergency medical dispatch training program (such as APCO, DOT, or Medical Priority Consultants) in place? If so, what type do you have and when was it adopted?

	Current	Date Adopted	Vendor
EMD (APCO)	____________	____________	________
EMD (Roth)	____________	____________	________
EMD (Other)	____________	____________	________
Informal Training/			
No Training	____________	____________	________
Alt Formal Training	____________	____________	________
Prior System	____________	____________	________

2. Emergency Call System Type

No-911 = County does (did) not have 3-digit emergency number available to residential customers and pay phones

Basic 911 = County does (did) have 3-digit emergency number but call centers not equipped with Automatic Location Identification (ALI) capability or less than 50% of residences are not ALI-enabled.

E911 = County does (did) have a 3-digit emergency number, call centers equipped with ALI capability, and over 50% of residences in county are ALI-enabled.

When was the first type of 911 service (either Basic or E911) adopted in the primary PSAP in your county?

MONTH/YEAR: ______________________________

If basic adopted first, when was E911 adopted?

MONTH/YEAR: ______________________________

NOTES:

PART III. Personnel/Organizational Questions

3. Which agency is primarily responsible for the call center?

Police Dept.	☐	Current	☐	1994
Fire Dept.	☐	Current	☐	1994
County	☐	Current	☐	1994
Other Agency.	☐	Current	☐	1994

DATE OF CHANGE

4. Are emergency medical calls taken in the same call center as all other emergencies? If now what other types of calls are grouped with emergency medical calls?

ALL	☐	Current	☐	1994
Police Emerg.	☐	Current	☐	1994
Fire Emerg.	☐	Current	☐	1994
Other	☐	Current	☐	1994

DATE OF CHANGE

5. What kind of personneltake telephone calls?

Police Officers	☐ Current	☐ 1994
Fire personnel.	☐ Current	☐ 1994
EMS	☐ Current	☐ 1994
Civilian telecommunicators	☐ Current	☐ 1994

DATE OF CHANGE

6. Is dispatching separate from call-taking☐ Yes ☐ No

<u>IV. Management</u>

7. How long has the current 911 Coordinator been in place?

8. Does your call center have affiliations with NENA or APCO?

9. Does anyone attend local or national meetings of these organizations?

<u>V. Adoption Costs</u>

10. What percentage of tonwships in your county need to, or did need to, approve substantial readdressing in order to adopt E911?

ADDITIONAL QUESTIONS FOR FOLLOW-UP SURVEY

C. CENTRALIZATION

4. Are all emergency calls for the county received at a single call center?
☐ YES ☐ NO

5. If yes, when was this “centralized” call facility opened?

MONTH/YEAR: ______________________ OR ☐ BEFORE 1990

6. If no, how many call centers are located in this county?

NUMBER: ______________________

7. Are these call centers linked by special telecommunication equipment (e.g., call forwarding)?
☐ YES ☐ NO

D. AMBULANCE SERVICES

8. Does this PSAP have Computer-Aided Dispatch (CAD) technology?
☐ YES ☐ NO

9. If yes, when was it adopted?

MONTH/YEAR: ______________________________

10. What types of ambulances are dispatched from this PSAP?

ALS	☐ Current	☐ 1994	☐ Not Dispatched
BLS	☐ Current	☐ 1994	☐ Not Dispatched

11. Who owns these ambulances?

ALS
☐ County
☐ Hospital
☐ Local Fire
☐ Municipalities
☐ Private ______________________________
☐ Other ______________________________

BLS
☐ County
☐ Hospital
☐ Local Fire
☐ Municipalities
☐ Private ______________________________
☐ Other ______________________________

12. Have they always owned these ambulances?
☐ YES ☐ NO

13. If no, what was the date of the change and who owned them before?

MONTH/YEAR: ______________________________

Owned by:
☐ County
☐ Hospital
☐ Local Fire
☐ Municipalities
☐ Private ______________________________
☐ Other ______________________________

14. What type of ambulance positioning is employed in this county?

LOCATION	TODAY	JANUARY, 1994	"SWITCH" DATE
Fire	☐	☐	__________________
Hospital	☐	☐	__________________
"Staged"	☐	☐	__________________
Not Managed	☐	☐	__________________

NOTES: