The Impact of Information Technology on Emergency Health Care Outcomes

by

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ABSTRACT: This paper analyzes the productivity of information technology in emergency response systems. "Enhanced 911" (E911) is information technology that links caller identification to a location database and so speeds up emergency response. We assess the impact of E911 on health outcomes using Pennsylvania ambulance and hospital records between 1994 and 1996, a period of substantial adoption. We find that, as a result of E911 adoption, patient health measured at the time of ambulance arrival improves, suggesting that E911 enhances the timeliness of emergency response. Further analysis using hospital discharge data shows that E911 reduces mortality and hospital costs.

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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, a phenomenon often cited as a driver of aggregate productivity growth and changes in wage inequality. Assessing the productivity impact of IT and the channels through which IT affects productivity has thus become a critical element in the evaluation of the sources of economic growth as well a host of public policies (Summers, 2000).

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* and *precision* (e.g., rapid and customized access to individual accounts or product-specific information). While such quality improvements may be reflected indirectly in economic quantities such as rising wages or increased willingness-to-pay (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 so the benefits from IT may vary according to the specific application and characteristics of the adopting organization (David, 1990; Bresnahan and Trajtenberg, 1995). Without detailed data about the types and uses of IT, empirical studies must aggregate over applications where IT has widely different costs and benefits, making policy analysis difficult.[1] Even when detailed data is available, estimates based on cross-sectional variation may be difficult to interpret, because 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 (Dinardo and Pischke, 1997; Athey and Stern, 1998).

Third, IT adoption may occur alongside potentially complementary changes in job design and human resource practices (Milgrom and Roberts, 1990).[2] Indeed, "skill-

[1] For example, see Brynjolffson and Hitt (1997), Black and Lynch (1998), Abowd and Kramarz (1999), and Bartel and Sicherman (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.
[2] For careful discussion of the empirical evidence, see Ichniowski, et al (1997), Bresnahan and Greenstein (1997), Levy, et al (2000) and Bresnahan, et al (2002).

biased technical change" is a popular explanation for observed changes in the wage structure (Krueger, 1993; Berman, et al, 1994; Autor, et al, 1998). Ignoring organizational design potentially omits a policy-relevant contributor to productivity and may lead to biases in estimating the impact of IT (Bartel, 1997; Athey and Stern, 1998).

This paper attempts to overcome 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 to analyze the impact of technology and job design on patient outcomes.[3] 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) 39 changes in technology and job design occur during the sample period, allowing us to compare the productivity of 911 centers before and after adoption; and (iv) the 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. With the lowest level of 911 technology, ("No 911"), citizens call a location-specific 7-digit telephone number that may differ for each emergency provider. An intermediate level enables access to emergency services by calling 911 ("Basic 911"). The highest level of technology, Enhanced 911 ("E911"), uses IT to link digital identification from incoming telephone calls to a database containing location information. Some 911 centers employ Emergency Medical Dispatching (EMD), in which call-takers follows a protocol to gather medical information, prioritize ambulance dispatch, and provide pre-arrival medical instructions.

In 1991, Pennsylvania enacted legislation facilitating the adoption of both 911 technology and EMD by county 911 centers. We analyze the impact of adoption by exploiting a unique dataset consisting of ambulance and hospital records for ambulance rides resulting in an emergency hospital admission in Pennsylvania during 1994 and 1996. These data include information about the location of the emergency, patient health

[3] Athey and Stern (2000) perform preliminary cross-sectional analysis using a subset of these data, focusing only on technology; this paper offers a comprehensive differences-in-differences analysis, incorporating the impact on health outcomes from changes over time in both IT and job design.

status as recorded by ambulance attendants upon arrival at the scene of the emergency, and (short-term) patient outcomes. This incident-specific information is combined with an original dataset recording the timing and circumstances of 911 technology and EMD adoption in all Pennsylvania counties. During the sample period, more than half of all counties adopt either a more advanced form of 911 technology or EMD, or both. 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.[4]

Since patients' health conditions deteriorate over time following the onset of cardiac symptoms, we expect that the faster ambulance response time resulting from E911 and/or EMD adoption will lead to improved intermediate health status (as measured by, e.g., blood pressure, respiration, and pulse rates) upon ambulance arrival. We evaluate the gains realized by counties who adopt within our sample frame and compare these gains to the productivity trend experienced by all the counties in Pennsylvania. Our preferred specifications include fixed effects for each locality as well as detailed time-varying controls. We employ several approaches to control and test for selectivity and heterogeneity in the marginal benefits of IT adoption. In short, we offer a "differences-in-differences" analysis of the impact of IT on emergency health care outcomes.

The principal finding is that E911 adoption is associated with significant improvements in the health status of cardiac patients. First, the adoption of E911 reduces the mortality probability as measured by health indicators at the time of ambulance arrival from .035 to .031. In other words, following E911 adoption, the ambulance arrives (and thus medical intervention begins) at a point where the probability of mortality is 11% lower. The effects of E911 on health status are most pronounced at the low end of the health distribution, and they are larger after E911 systems have been in place for several months (suggesting that learning-by-doing may be important). We find no evidence that EMD impacts health status directly or as the result of an interaction with E911. Each of these effects is robust to a variety of alternative control structures, including a number of time trend specifications, alternative sample definitions, and the

[4] In focusing on cardiac emergencies, we follow several studies about medical care output and productivity measurement (McClellan and Newhouse, 1997; Cutler, et al, 1998, 1999; Triplett, 1999). Only a few medical studies analyze the impact of 911 on medical outcomes. In general, sample limitations make it difficult to draw inferences. One exception is Joslyn, et al (1993), who found that mortality from out-of-hospital cardiac arrest decreased significantly as a result of 911 adoption, due in large part to decreased response time. This study did not focus on E911.

inclusion of interaction effects between E911 and demographic variables.

A large clinical literature (discussed below) documents the benefits of timeliness for health outcomes. We confirm these findings in our data by analyzing the effects of E911 adoption on outcomes provided in hospital discharge data. While this evidence is less precise, we find that the short-term mortality rate and hospital costs are reduced significantly after E911 adoption. From a welfare perspective, even though E911 is thought to be useful over a much wider range of emergencies than the condition considered here, our estimates suggest that the marginal benefits of IT in 911 centers to cardiac patients may, by themselves, justify most of the cost of adoption.

The paper proceeds as follows. In Section II, we describe the institutional details of the pre-hospital emergency response system. Section III develops a simple model of emergency health care production and an econometric model to guide the estimation. Sections IV and V overview the data, the adoption process, and the demographics of counties by adopter type. Section VI presents the results. A final section concludes.

II. Information Technology and Job Design in Emergency Response Systems

II.A. Emergency Response Systems: An Overview

An Emergency Response 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 were not specialized to emergencies) or to individual service agencies (whereby callers needed to locate the telephone number for the appropriate agency), resulting in inappropriate responses to emergencies (Gibson, 1977; Siler, 1988). Following a model first developed in Europe, 911 systems were introduced into the U.S. in 1968. While the scope and details vary, systems typically operate as follows:

- ♦ 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.
- ♦ Call-takers may provide additional instructions to the caller in some systems.

Emergency response systems are almost always public and so differ in many ways from service firms in the private sector.[5] Despite these differences, emergency response systems can be thought of as a special case of "help desks," one of the fastest growing uses of IT in the service sector. Help desks are designed to provide: (a) timely response by organizations to customers; (b) 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.

Consider the importance of timeliness, precision, and resource allocation in emergency health care. The first component of the "chain of survival" advocated by the American Heart Association is early access to emergency medical services. Clinical studies suggest that the timeliness of administering medical procedures such as CPR and defibrillation decreases the mortality rate from out-of-hospital cardiac arrest.[6] Until recently, defibrillation – electrical shock therapy to "reset" the electrical activity of the heart – required equipment available only on Advanced Life Support (ALS) ambulances, and only trained paramedics could provide treatment. Further, the efficacy of pharmaceutical treatments like thrombolytics, used in one-third of heart attack cases in 1995, decreases linearly with delay time (Cutler, et al, 1999). Precise information about each emergency allows resources to be conserved for time-sensitive emergencies.[7]

II.B. Information Technology and Job Design

In contrast to many other applications where IT and job design are difficult to compare across organizations, emergency response systems faced a well-defined set of choices during the 1990s. Industry participants recognized three primary IT alternatives (No 911, Basic 911, and E911), as well as the option of implementing EMD. No 911 systems are typically decentralized. Individual municipalities may have their own seven-digit telephone number, and police and fire departments often forego the use of

[5] Several externalities are associated with emergency response. Not only does public provision lower the cost to bystanders of providing the public good of reporting emergencies, but public control over emergency response facilities is critical during extreme public emergencies (e.g., nuclear accident). Privatization experiments have met with little success; one Pennsylvania county did attempt to privatize in the late 1990s but discontined the initiative shortly thereafter, resulting in a lengthy litigation.

[6] For example, Larsen, et al (1993) finds that, from a level of 0.33, the survival probability falls at the rate of .023 per minute that CPR is delayed, .011 per minute that defibrillation is delayed, and .021 per minute that an ALS ambulance is delayed. See also Lewis et al, 1982; Cummins et al, 1992; Bonnin, et al, 1993; and Tresch, et al, 1989.

[7] A more indirect benefit from precision is the reduction of unnecessary "lights-and-siren" responses which may reduce incidental traffic accidents (Gibson, 1977; Smith, 1988; Brown and Sindelar, 1993).

specialized call-taking personnel.[8] A Basic 911 system requires installation of dedicated telecommunications services for emergency callers, and is designed to reduce the time from the first awareness of an emergency and contact with an emergency agency. Adoption of Basic 911 is often associated with centralization (at the county rather than municipal level), allowing for specialization. A potential cost to centralization is unfamiliarity by call-takers with distant or remote areas. All Pennsylvania call-takers in 911 centers must, by law, receive a minimal level of (fairly) standardized training.[9]

E911 was introduced during the 1980s, and the technology is marketed to emergency response systems by large telecommunication vendors. To implement the Automatic Location Identification features ("ALI") of E911, counties develop a database of unique street addresses for every residence in a county, often requiring readdressing to eliminate duplicates, as well as the creation of new street addresses for many rural areas. This database includes precise information about the location of a telephone in a building or public place, and can potentially track individual health issues or disabilities.

E911 technology is associated with a number of benefits. First, even when a caller knows their location and provides precise directions, this information takes time to communicate. Callers may experience panic or fear, or be otherwise unable to provide precise information (e.g., children, non-native English speakers, or those unfamiliar with a particular area). Furthermore, when locational information is communicated electronically, more time is available to gather information about incident severity or to provide pre-arrival instructions. As well, detailed geographic knowledge of an area is no longer essential, increasing the returns to centralization. Finally, by establishing a precise electronic database, E911 increases the potential for coordination with ambulance dispatchers, facilitates the provision of private emergency response services marketed to the elderly and high-risk individuals,[10] and enables the adoption of even more advanced technologies (e.g., GPS-assisted computer-aided dispatch).[11]

Now consider job design for medical emergencies. In the absence of EMD, job

[8] No 911 is thus a technological and organizational choice; we use the word "technology" for simplicity.

[9] Basic 911 also facilitates the adoption of several related technologies, such as Automatic Number Identification and automatic call recording.

[10] 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.

[11] Unfortunately, we cannot estimate the distinct impact of GPS. Only 4 counties explicitly adopted GPS by the end of 1996 (though over half of all counties had adopted some GPS technology by June, 2000).

design is relatively unstructured, and the call-taker's main responsibility is to provide address and severity information to ambulances. Typically, providing medical advice is prohibited or discouraged. Under EMD, however, call-takers use emergency-specific "protocols" which guide call-takers through the process of eliciting information and providing emergency medical instructions. Call-takers also provide instructions for preparing the emergency site for ambulance arrival. These interventions reduce the time it takes to perform key medical procedures, and reduce the probability that inappropriate procedures are performed prior to ambulance arrival. EMD may also improve precision by increasing call-taker accuracy at assessing the nature and severity of emergencies, and so increase the likelihood of dispatching appropriate equipment.[12]

The returns to adopting EMD and advanced IT may be interrelated. One hypothesis is that E911 and EMD are complements.[13] E911 automates the collection of location information, allowing for more intensive and effective use of the EMD protocols, and the use of higher-skilled workers in operate E911 systems may increase the effectiveness of EMD protocols. Alternatively, E911 and EMD may be substitutes. Training to use the computer system may "crowd out" time and attention for EMD training, and the use of lower-skilled workers for the "automated" E911 system may increase the costs of implementing EMD. The relative importance of these effects is an empirical question.

III. The Empirical Framework

III.A. The Production Function for Health Status

This paper relies on two types of health status measures for cardiac patients to assess the productivity of 911 technology and EMD. First, we use health measures observed at the time of ambulance arrival to evaluate the relationship between IT and response time. Second, we analyze longer-term health outcome measures. This section outlines a simple model of emergency intervention and health production to organize the analysis.

At time τ=0, a patient experiences cardiac distress. The initial severity of this incident is determined by ξ. The ambulance arrives at time $\tau = \tau^A$. Figure A depicts health status, $h(\tau;\xi,\tau^A)$, where higher values indicate more severe symptoms. There are

[12] 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).

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

two effects of early arrival. First, the patient is observed at an earlier point in time, so that indicators of a patient's health status at that time, $h(\tau^A;\xi,\tau^A)$, should appear less severe. Second, early administration of treatment slows the deterioration of the patient's health status, leading to improvements in health status measured at later times.

A more sophisticated 911 system improves health by improving the distribution of τ^A. To capture this, we construct a measure of "intermediate health status" at time τ^A based on vital statistics (pulse, respiration, responsiveness, and blood pressure) measured at the incident scene. As Figure A indicates, better intermediate health status should be associated with improved health outcomes.[14] The expected value of $h(\tau^A;\xi,\tau^A)$ should decrease when the distribution of τ^A improves because health status deteriorates over time (even if early intervention does not affect subsequent mortality). Indeed, if the adoption of IT improves response time from τ_H^A to τ_L^A, the improvement in the patient's health status measured at ambulance arrival, $h(\tau_L^A;\xi,\tau_L^A)-h(\tau_H^A;\xi,\tau_H^A)$, could be larger or smaller than the improvement in the patient's health status measured at a later time τ^F, $h(\tau^F;\xi,\tau_L^A)-h(\tau^F;\xi,\tau_H^A)$.

However, the clinical medical literature suggests that improvements in timeliness should, in fact, have significant effects on longer-term health. Thus, E911 should impact these outcomes. The second step of our analysis considers such evidence. Since we have limited measures of health status in the hospital, we focus on the change in the probability of mortality prior to τ^F as well as hospital charges.[15] To interpret the latter, observe that a shift in the distribution of health has ambiguous consequences on health expenditures (Meltzer, 1997). While improved health for moderately sick patients tends to lower expenditures, the improved survival rate for sick patients both increases the number of patients and the average costs of those patients.

III.B. The Estimation Strategy

Our estimation approach is based on "differences-in-differences": we evaluate how patient health outcomes change within counties that change their level of 911 technology or EMD during our sample, relative to a time trend in health outcomes for counties who do not switch or who switch at different points in time. This section formalizes and interprets the assumptions required to make this empirical strategy valid.

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[14] Thus, we scale our index in terms of 48-hour mortality.

[15] 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 (Herlitz, et al, 1995).

We observe the health status of individual patients within a given county (with a known level of 911 technology and job design), and, within that county, we observe the location of the incident at the "MCD" (minor civil district) level, which may have its own idiosyncratic characteristics. Consider the following notation:

Notation	Interpretation
(t,i,j,k)	Date t, county $i \in \{1,..,I\}$, MCD $j \in \{1,..,J\}$, patient $k \in \{1,..,K\}$.
$\mathbf{s}_i^t$	Indicators for technology-EMD systems (county i, date t).
$\mathbf{x}_k$	Observed patient and incident characteristics for patient k.
$\mathbf{z}_j^t$	Observed MCD characteristics for MCD j at date t.
χ_i^t	Unobserved 911 center quality and characteristics of county i at date t.
ψ_j	Unobserved MCD characteristics (i.e. geography and infrastructure).
ξ_k	Unobserved incident severity.

Motivated by the last section, a patient's measured health status can be written:

$$HEALTH_{i,j,k}^t = f(\mathbf{s}_i^t, \mathbf{x}_k, \mathbf{z}_j^t, \chi_i^t, \psi_j, \xi_k) \qquad (1)$$

Our first assumption decomposes county quality into a fixed component and a time-varying component, and assumes that the latter is additive and constant across counties:

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

Section VI.B.4 relaxes (A1) in several ways. We allow the time trend to vary with observable location characteristics or with a county's initial 911 technology level; we also allow for individual counties to experience "shocks" that are serially correlated and correct our standard errors for correlation within a county over the entire sample period.

Now consider the relationship between the unobservables and the 911 system. We allow for the possibility that 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 (e.g., some counties face political constraints that affect the provision of other public goods, and these goods affect the average response time in the county). However, we assume that the *incremental returns* to adopting different 911 systems are the same across counties (i.e., E911 saves 30 seconds in every county), as follows:

(A2) f is additively separable in χ_i^t and ψ_j.

Without (A2), our approach identifies the average returns among counties changing their 911 systems during the sample period. However, if (A2) fails, the selection of counties that adopt may have returns different than the average level of returns. To address this concern, Section V presents evidence concerning the representativeness of counties adopting 911 systems during our sample; as well, we perform a specification test evaluating (A2) directly. Finally, even if adoption is systematically associated with returns, our sample period is in the "middle" of the adoption process, and so the estimates identify the impact of IT for locations similar to an average Pennsylvania county.

We also impose restrictions on unobserved patient severity. While we allow 911 technology to be correlated with the average health of patients in a county, we assume that within-county changes in patient severity are uncorrelated with the 911 system:

(A3) Within a county, ξ_k is independent of $\mathbf{s}_i^t$, conditional on $\mathbf{x}_k$ and $\mathbf{z}_j^t$.

This assumption may be violated if changes in the 911 system are associated with changes in the distribution of patients (e.g., if adoption results in greater usage by more marginal patients). Although definitive evidence about the validity of this assumption is difficult to construct, we find no evidence for increased patient volume after E911 adoption, and we control for county-level patient volume in our empirical analysis.

Because higher levels of technology and training are more common later in our sample, we control for changes in the distribution of health outcomes over time. The time trend is identified in our sample without parametric restrictions, in part because:

(A4) For some counties *i*, $\mathbf{s}_i^t$ is unchanged over the sample period.

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

Under (A1)-(A4), referred to as "the assumptions of the fixed effect model," the average effect of *changes in* the 911 regime on health outcomes are identified. Imposing a linear functional form for *f*, letting c_i be the fixed effect for each county and q_t be a quarterly calendar dummy, our baseline empirical specification is therefore:

$$\begin{aligned} HEALTH_{i,j,k}^t = c_i + q_t + BASIC_{i,t}(\alpha_{BASIC} - \alpha_{NO911}) + E911_{i,t}(\alpha_{E911} - \alpha_{NO911}) \\ + EMD_{i,t}\alpha_{EMD} + \mathbf{x}_k \boldsymbol{\beta} + \mathbf{z}_j^t \boldsymbol{\gamma} + \psi_j + \xi_k \end{aligned} \tag{2}$$

We use this model to test hypotheses about the impact of 911 systems ($\alpha_{\text{E911}} - \alpha_{\text{NO911}}$, $\alpha_{\text{BASIC}} - \alpha_{\text{NO911}}$, and α_{EMD}) and evaluate several of our maintained assumptions. For example, by allowing $\boldsymbol{\alpha}$ to vary with the time from the adoption date, we can check to seen whether the benefits from adoption begin to appear prior to the adoption date (evidence of selectivity) and whether the benefits from adoption are realized with a lag. We can additionally test for interactions between 911 technology and EMD. Finally, the model is over-identified, since the effect of switching from No 911 to E911 can be evaluated in two distinct ways. One can sum the effects associated with going from No 911 to Basic, and Basic to E911, or evaluate the effect of switching from No 911 to E911 directly. Under (A2), these quantities are the same, a testable restriction of our data.

IV. The Data

To implement the econometric approach described in Section III, we analyze a setting characterized by the availability of unusually rich data, as well as an institutional environment where the assumptions of the fixed effect model may be plausible. This section describes the data; the next section provides institutional information and empirical facts justifying the assumptions of the fixed effects model.

IV.A. Data Sources

Our first source is a novel 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 rides matched to hospital admissions (out of an annual total of about 1.7 million hospital admissions in Pennsylvania). For each patient, we observe:

- 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, whether the response was in "lights-and-siren" mode, the type of ambulance and ambulance personnel);
- Health indicators upon ambulance arrival 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);
- A (confidential) code for the hospital to which the patient is transported;
- Diagnostic information at the time of hospital admission;
- Hospital discharge and billing records (e.g., discharge status,

disaggregated charges, patient insurance type and billing zip code).

Most of our analysis focuses 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. We supplement the PA EMS dataset with data gathered from a retrospective telephone 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 PSAP Survey").[16] For every 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. Each of the 67 counties within Pennsylvania completed a survey, providing information about the month and year of adoption.[17] Thus, we observe the 911 technology (NO 911, BASIC 911, or E911) and the presence or absence of EMD for every county in Pennsylvania at each point in our sample period (Table 1 provides precise definitions for each type of adoption). Finally, we incorporate geographic variation by gathering demographic and weather data at the zip code, MCD, hospital, and county levels (Table 1 lists variables and sources).

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 where the "suspected illness" reported on the ambulance report was cardiac, and only patients who are diagnosed, upon admission to the hospital, with a cardiac condition (i.e., 3-digit ICD-9 Diagnostic Codes in the range 400-459, including acute myocardial infarction, cardiac dysrhythmias, hypertension, and heart failure).[18] We eliminate observations satisfying one or more of the following criteria:

- Emergencies which do not require "lights-and-sirens" on both the outgoing dispatch call and during the ambulance transport to the hospital;
- Patients less than 20 years old and pregnancies;
- Transports from one medical facility to another;

[16] The follow-up survey verified adoption dates and filled in entries incomplete from the first survey. Overall, the MIT PSAP Survey provides a more comprehensive look at Pennsylvania 911 centers than was available for our earlier cross-sectional analysis of the PA EMS dataset (Athey and Stern, 2000).
[17] The initiation of either a higher level of 911 technology or EMD is pivotal event for most call centers (see, e.g., www.ccia.com/~lawco911/index.html); typically, respondents provided detailed descriptions of the factors that delayed adoption and the perceived benefits associated with adoption.
[18] We choose a broad set of cardiac diagnoses, since a patients' in-hospital diagnosis reflects their health on arrival, itself a function of emergency response timeliness. Our results are, however, robust to narrower sample definitions.

- Incidents in the two large metropolitan areas of Pennsylvania, Philadelphia and Pittsburgh;[19]
- 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 19,746 observations, with 55% of patient incidents in 1994. Our qualitative results remain similar when we include any of these groups in our selection criteria or narrow the diagnostic criteria to condition on a smaller range of cardiac-related diagnoses.

IV.C. Variables and Summary Statistics

For the variables used in our analysis, Table 1 provides variable names and definitions, while Table 2 reports summary statistics. The demographic, incident, and location characteristics are self-explanatory. However, the health status outcome measures require some discussion. We use several different health outcome measures, varying along two dimensions. First, they differ with respect to *when* they are measured relative to the emergency incident. We refer to measures observed at the time of ambulance arrival as measures of intermediate health status, and measures observed after hospital admission, such as mortality and hospital charges, as hospital measures. Second, while some measures are "raw" indicators such as blood pressure and mortality, others are constructed "health indices" that aggregate the raw health status measures.

Raw Patient Health Outcome Measures

Our raw measures of intermediate health status, recorded in the ambulance, include systolic blood pressure (BLOOD PRESSURE), the rate of respiration (RESPIRATION), pulse rate (PULSE), and the Glasgow coma score (GLASGOW).[20]

Unfortunately, hospital outcome data are available *only* for the first hospital to which the patient is admitted. If (a) the patient is transferred from the initial hospital to a more advanced hospital with cardiac facilities or (b) the patient if discharged and readmitted in

[19] We exclude Philadelphia and Pittsburgh because (a) neither city experienced adoption during our sample period and (b) the trend in health outcomes associated with dense urban areas may differ from that experienced by suburban or rural areas.
[20] Though not the only available health status measures, (e.g., we do not use EKG readings), each has significant explanatory power for mortality from cardiac incidents. The first three measures are self-explantory; the Glasgow Coma score is a specialized emergency medicine index, ranging from 3-15 (higher scores indicate lower severity), reflecting patient alertness and responsiveness (www.trauma.org).

a short amount of time, our data will indicate only that the patient was discharged to hospital or home, respectively.[21] Thus, we restrict attention to "medium-term" mortality, 6 HR MORTALITY (mean = .008) and 48 HR MORTALITY (mean = .035). The effects of pre-hospital care should be most pronounced during the initial hours following an incident, and such medium-term measures likely reduce the possible censoring bias described above. Finally, we measure TOTAL COSTS, equal to reported inpatient charges, adjusted by the hospital-specific annual Medicare cost-to-charge ratio.

Calculated Patient Health Outcome Measures

We convert the raw measures of intermediate health status into an index which (a) accounts for non-linearities and non-monotonicities 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) is scaled according to the predicted probability of short-term mortality.

There is a well-developed clinical emergency medical literature devoted to developing indices, or "scores," of patient health based on various intermediate health status measures.[22] 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), we construct several of our own based on leading scores designed for critical care, using four raw measures of intermediate health status.[23]

We begin by creating two indicator variables based on whether a patient is in the "high-risk" region in terms of a single health measure: HIGH RISK BLOOD PRESSURE (equal to 1 if systolic blood pressure is less than 90) and HIGH RISK PULSE (equal to 1 if the pulse rate is less than 40). The correlation between these measures is .68.

Second, we calculate an index of intermediate health status, HINDEX, as follows. We first create a set of categories for each of our four raw health measures based on (a)

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[21] Only 0.6% of our sample transfers to another hospital within 6 hours, while 4.8% transfers to another hospital within 48 hours. 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 explore the impact of controlling for the type of hospital discharge in Table 7.

[22] These scores are designed to aid medical decision-making and provide benchmarking tools. For any given scoring method, health measures are categorized into ranges, with each range being assigned a number; the score is a weighted average of these score components (Svirbely and Sriram, 2001).

[23] 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.

the critical cut-off points for BLOOD PRESSURE, RESPIRATION, and GLASGOW suggested by one leading scoring system (called the Revised Trauma Score (RTS) system)[24] and (b) HIGH RISK PULSE.[25] We then perform a probit regression of 48 HOUR MORTALITY on the full set of these categorical variables (reported in Appendix A).[26] HINDEX is calculated as the predicted value of 48 HOUR MORTALITY from this regression (its mean is.035, equal to the sample mortality probability). Thus, HINDEX can be interpreted as the 48-hour mortality 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.

V. Characteristics of Pre-Sample, Within-Sample, and Post-Sample Adopters

Our estimation approach is based on county or MCD fixed effects, thereby avoiding the familiar biases of cross-sectional comparisons. To validate our approach, it is important to understand how county adoption decisions relate to county characteristics. Specifically, our results will be biased if the incremental returns to adoption vary across counties and adoption is systematically related to such heterogeneity. In particular, counties with higher-than-average benefits may be more likely to adopt. However, the environment and time period we examine suggest that within-sample adopting counties likely realize returns that are close to the average level of population returns.

V.A A Description of the Adoption Process

Pennsylvania passed the Public Safety Emergency Telephone Program ("PSETP") in 1991, reducing the administrative costs and political impediments of adopting Basic 911 and E911 at the county level.[27] The Act reduced the monetary costs of adoption in two ways. First, it authorized each county to implement a telephone tax on its residents to

[24] Although this score is designed for trauma, the cutoffs used are similar to those used in cardiac scores, and it is based on the vital signs recorded at the scene of an incident. See Champion, et al (1981, 1989).

[25] HIGH RISK PULSE is not included among the measures in the RTS system. However, HIGH RISK PULSE is correlated with mortality and included in alternative scoring systems, and so we choose to include it in our analysis.

[26] The mortality regression results are sensible from the perspective of the clinical literature, with significant reductions in mortality associated with CAT4(GLASGOW), CAT4(BLOOD PRESSURE) and HIGH RISK PULSE. While multicollinearity makes interpreting individual coefficients difficult, there is a monotone relationship between survival and severity categories in more parsimonious specifications (Athey and Stern, 2000). All of our results are robust to the use of more or less detailed health score specifications.

[27] The legislation explicitly states that the toll-free number 9-1-1 is to be provided with the goal of reducing response time to emergency aid, and that authority and responsibility is vested in county governments with encouragement from the state. See the Pennsylvania Emergency Management Agency (www.pema.pa.state.us) and www.state.pa.us/PA_Exec/PEMA/programs/911/chang120.htm.

pay for 911 services (between \$0.75 and \$1.50 a resident depending on the size of the county). Second, it created six EMS regions within Pennsylvania, authorizing regional EMS coordinators to increase the level of training and skill investment in 911 centers.

At the beginning of 1992, only four counties throughout the state had implemented both E911 and EMD; by the late 1990s, both were fairly pervasive. By 2000, only one Pennsylvania county did not have either Basic 911 or E911, and EMD was in place in over 75% of Pennsylvania counties. The period between the beginning of 1994 and 1996 was a crucial adoption period, when over half of all counties switched either their level of technology, adopted EMD, or both. Many of the counties who do not switch during the 1994-1996 period either adopted in 1991-1993 or in 1997-1998.

To understand the sources of heterogeneity in adoption time, consider the steps required to adopt E911 (for more detail, see Pivetta (1995)). First, counties must complete a time-intensive and labor-intensive process of assigning precise addresses to all county residents, creating new maps, and developing a computerized database. Re-addressing requires coordination with local post offices and public utilities, and typically must be approved by each municipality in a county. Prior to the passage of PSETP, municipalities were unwilling to undertake such expenditures themselves and counties lacked specific authority to act. Further, the telephone equipment, address database, and call-taker workstations must be procured and installed. Though systematic cost start-up cost data is unavailable, we estimate, from several case examples, that the start-up costs for a typical county ranged between \$1 million and \$4 million.[28] Nationally, 911 technology levels seem to be systematically related to certain county characteristics, such as population, suggesting that the costs of adoption play an important role in the adoption process (Athey and Stern, 1999; 2000).[29]

To evaluate the drivers of adoption in Pennsylvania, we interviewed 911 system managers, state administrators, and examined industry publications. Our interviews strongly support the hypotheses that while PSETP played an important role in facilitating

[28] For example, Berks County, PA (pop. 336,000) reports E911 start-up costs of approximately \$3 million, and annual (total) operating costs of over \$2.3 million, of which only a small portion is associated with the incremental costs associated with E911; all of these expenditures are primarily funded through a local telephone line tax. Employing nine call-takers and an administrative staff, the Berks County E911 Center is slightly larger than the average center in our sample. See http://www.readingpa.com/911.

[29] In addition to population, our earlier results, based on a cross-sectional national sample of about 800 911 systems in 1995, suggest that several demographic factors, including political voting patterns, significantly impact the probability of adoption (Athey and Stern, 1999; 2000).

adoption, the precise timing of adoption was mostly unrelated to the perceived health benefits. For example, some counties experienced substantial delays in completing the addressing process, whereas other counties faced delays due to long negotiations with municipalities and police departments over the control and employment of call-takers.[30]

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 EMS Regions 1 and 4 adopt EMD relatively early in our sample period, although these two regions display quite different characteristics.[31]

We additionally investigated potential changes in the 911 system or the health care infrastructure which might confound the analysis of technology adoption and EMD. In terms of ambulance infrastructure, we found that the following factors did not change for more than a single county during our sample: the overall number of ambulances and ALS ambulances (plus or minus one), and the ownership or organization of the ambulance system.[32] 911 systems might also have changed their overall organization at the same time that E911 was adopted. Indeed, while centralization or the opening of a completely new facility is quite common among the adopters 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 adopters 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. Even when a 911 Coordinator was hired in conjunction with adoption, the individual typically began working at least six months before the E911 system went into effect.

V.B Comparing Characteristics of Counties by Adoption Patterns

Consider the specific changes in 911 systems that occur during our sample period, 1994-1996. 22 counties begin the sample with NO 911 (of which 8 shift to BASIC and 9 shift to E911 between the beginning of 1994 and the end of 1996). Out of the 20 counties

[30] Delays often involved negotiations over peripheral issues. In one county, E911 adoption was delayed over negotiations with a municipality over the provision of state police for highway patrol.

[31] 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.

[32] While counties differ as to whether ambulances are public or private and concentration of ownership, no changes in the organization of ambulance delivery alonside technology or EMD adoption occur during our sample. As well, we control for the number of distinct ambulances serving each MCD each quarter.

that begin the sample with BASIC, 14 of these counties adopt E911 during the sample period. By the end of 1996, 46 out of 65 counties included in the sample have adopted the E911 technology. Among 51 counties without EMD at the beginning of 1994, 30 adopt EMD during the 1994-1996 sample period.

The non-switchers can be usefully divided into two groups: those who adopt 911 technology prior to 1994 (pre-sample adopters) and those who adopt the technology after 1996 (post-sample adopters). Each of the three groups--within sample adopters, pre-sample adopters, and post-sample adopters--contains one third of the counties. We further subdivide the pre-sample adopters into the very early adopters (before 1992) and the early adopters (1992-1993). As well, recall that there are three distinct types of technology switching: No 911 → Basic 911, No 911 → E911, and Basic 911 → E911.

Table 3 presents county-level average characteristics for each of seven different "regimes," according to their pre-sample technology and their adoption behavior between 1994 and 1996.[33] While these groups are fairly similar, several differences are useful to note. First, counties who maintain Basic 911 or switch from No 911 to Basic during the sample period have smaller populations and lower densities than the sample average. As well, while within-sample Basic 911 adopters have average per capita income, counties maintaining a low level of technology have a slightly lower-than-average per capita income. In contrast, pre-1994 E911 adopter counties are larger, more densely populated, and have slightly older patients (each effect is pronounced for adopters during 1992 and 1993).[34] Together, these patterns suggest that willingness to incur the fixed costs of E911 adoption is lower in smaller, more rural counties.

Counties adopting E911 (from either Basic or No 911) during our sample period display characteristics similar to the "average" Pennsylvania county along most dimensions. The only significant difference is that counties switching from No 911 to E911 are associated with somewhat lower incomes, potentially highlighting the effect of the PSETP in encouraging adoption in poorer counties. Overall, these demographic patterns accord with the fact that the adoption observed within our sample is centered in

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

[34] It is useful to note, however, that Philadelphia and the near suburbs of Pittsburgh (two of the densest and most populous areas in Pennsylvania) are *post-1996* adopters. Recall that we exclude these areas since we believe that the health productivity trend may be different in these highly urbanized areas.

the middle of the overall distribution of adopters. Finally, while a more systematic analysis of mortality will be conducted in the next section, it is useful to note that the earliest adopters of E911 are associated with the highest mortality rates, and that Basic to E911 adopters are associated with a somewhat lower mortality probability.

VI. Empirical Analysis of the Impact of 911 Technology and Job Design

Our empirical analysis proceeds in several steps. We begin with our principal 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 post-adoption learning, interaction effects between 911 technology and job design, and the relationship between 911 technology adoption and alternative theories of technological diffusion. We also investigate sources of potential bias and selectivity. Finally, we turn to hospital outcome measures, including short-term mortality and hospital costs. Our main result is that counties that adopt E911 (either by itself or in conjunction with EMD) experience a significant improvement in pre-hospital emergency response productivity.

Except where noted, the analysis focuses on the probability of mortality or a poor intermediate health status outcome and employs either a linear or log-odds functional form.[35] Since the incidence of these negative events is small (e.g., the average 48-hour mortality probability is .035), elasticities with respect to these measures will be substantially larger (in absolute value) than those with respect to survival (or positive outcomes). The tables therefore report regression coefficients whose (absolute) value does not depend on whether the analysis is in terms of survival or mortality, and we are careful to interpret coefficient and elasticity magnitudes by noting when they depend on the "direction" of the dependent variable.

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

We begin our analysis with intermediate health status measures based on a single indicator. Table 4A focuses on HIGH 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, controlling for a time trend using quarterly dummy variables. Not only is there no statistical relationship between 911 technology and

[35] Except where noted, regressions report robust standard errors, adjusted for clustering by county-quarter groups.

outcomes, but the coefficients are extremely small (and, for E911 and EMD, the point estimates are positive). In contrast, (4A-2) employs the differences-in-differences strategy, including a fixed effect for each county in the sample along with the time trend. Here we find a large and statistically significant relationship between E911 and HIGH RISK BLOOD PRESSURE.[36] E911 adoption decreases the probability of HIGH RISK BLOOD PRESSURE by .04 (the mean is just over .10). Further, we can reject the hypothesis that E911 offers no incremental benefit over BASIC 911. These findings are strengthened in (4A-3) when we incorporate 1997 MCD fixed effects, each of which is entirely contained within individual counties. Including MCD fixed effects significantly improves the overall fit; a specification test rejects the restrictions imposed by the county-level fixed effects model in favor of MCD fixed effects.

These results suggest that controlling for the level of health status in a location is critical for estimating the marginal impact of IT in improving health status. Variation in average health across locations likely arises because of demographic differences (such as an older population) and infrastructure differences, such as the distance of patients to hospitals and ambulances and the level of traffic. Geographic controls (such as population, density, and per capita income) do not explain this heterogeneity in health. We thus rely on models including fixed geographic effects, so that the estimates reflect the average realized benefit to adoption for counties that adopt during our sample period.

Table 4B explores these findings in more depth, by including a rich set of control variables and considering alternative dependent variables. In addition to detailed patient characteristics (including demographics associated with the patient's home zip code), we control for changes over time in the ambulance infrastructure and the call volume experienced in each county in each month. CALL VOLUME provides a proxy for changes in the distribution or volume of patients that might occur after E911 adoption.[37] We also control for daily local weather, which might otherwise introduce correlation among neighboring localities in a given time period. Except where noted, the remainder of our empirical work on intermediate health status employs the MCD fixed effects specification with these controls. Comparing (4B-1) to (4A-3) demonstrates that the

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[36] The time trend consists of eight quarterly dummies, allowing for more nuance than a linear time trend, and incorporating seasonality in health outcomes and emergency responsiveness. The E911 results are robust to dropping this time trend (indeed, the size and significance of the E911 coefficient increases a bit).
[37] In fact, CALL VOLUME is *not* sensitive to E911 adoption, suggesting that the patient pool is not significantly impacted by adoption.

inclusion of additional controls does not affect our main findings.[38] As well, (4B-2) shows similar results for an alternative single-dimensional intermediate health status measure, HIGH RISK PULSE; the probability of HIGH RISK PULSE decreases by .035 after E911 adoption (the average of HIGH RISK PULSE is .065). Similar results obtain for other measures, including respiration and the Glasgow score, and each of these results is robust to alternative specifications, including a fixed-effects logit specification, and the inclusion or exclusion of demographic and incident location controls. In other words, E911 adoption is associated with a significant reduction in the share of cardiac emergency patients observed with life-threatening intermediate health status indicators.

We next consider our index of intermediate health status. HINDEX is the predicted probability of 48-hour mortality based on information from the individual intermediate health status measures, described in IV.C.1. We follow the bulk of research on survival probabilities and use the log-odds ratio, $\text{LL HINDEX} = \ln\left(\text{HINDEX}/(1 - \text{HINDEX})\right)$, ensuring that the probability of survival predicted by the specification falls between 0 and 1 and reducing the skew of HINDEX (Dawson-Sanders and Trapp, 1994). Similar to the raw measures, (4B-3) shows that E911 adoption is associated with a significant reduction in HINDEX, while both BASIC and EMD have effects that are insignificant and small in magnitude. The probability derivative of HINDEX with respect to E911 is .004, an 11% reduction in the predicted probability of mortality.[39]

As described above, the critical factor driving this result is the inclusion of fixed effects for individual geographic areas. Without them, the predicted impact of E911 is noisy and insignificant. Within fixed-effect models, our results are quite robust to alternative specifications. For example, the E911 coefficient remains significant and of similar magnitude (in terms of mortality elasticities) when the dependent variable is HINDEX or ln(HINDEX), and we can include or exclude detailed patient characteristics or time-varying incident characteristics with no qualitative impact on the results. As well, in all specifications, we reject the hypothesis that BASIC=E911 at the 1% level.

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[38] Several findings are associated with the control variables. Health status is lower for patients who are male, in higher age categories, or whose home zip code contains a high percentage of black residents. Other factors, notably the weather characteristics and overall call volume, tend to be statistically and quantitatively insignificant. Inclusion or exclusion of these controls does not impact the E911 results.

[39] The probability derivative implied by a coefficient β is equal to $(.035)(1-.035)^*\beta$ (for discrete variables, this is a close approximation). By construction, elasticities with respect to the survival probability (i.e. (1 – HINDEX)) are much smaller in magnitude.

As suggested in Section III.C, it is possible to perform a specification test by estimating whether the returns to switching from No 911 to Basic (λ_{NO911_BASIC}) plus the returns to switching from Basic 911 to E911 (λ_{BASIC_E911}) are equal to the returns to switching from No 911 to Basic 911 (λ_{NO911_E911}). We test this by estimating (4B-3) but estimating a separate coefficient for each switching pattern. The estimates (with standard errors in parentheses) are $\hat{\lambda}_{NO911\_BASIC}$=–.012 (.046), $\hat{\lambda}_{BASIC\_E911}$=–.091 (.040), and $\hat{\lambda}_{NO911\_E911}$=–.112 (.041); we cannot reject the hypothesis that $\lambda_{NO911\_BASIC} + \lambda_{BASIC\_E911} = \lambda_{NO911\_E911}$.

Taken together, our results are consistent with the theory that timeliness in emergency response services is quite sensitive to the time it takes to establish and dispatch an ambulance to a precise location, and that timeliness has been improved by the adoption of advanced information technology. If the primary benefits came from standardization (i.e., the 911 number itself), then Basic and E911 should have a similar impact.[40] Our EMD findings are less conclusive, since the benefits of EMD may be realized in terms of treatment after arrival. However, our results do not support the hypothesis that EMD leads to large improvements in *timeliness* for cardiac emergencies (for example, through improved allocation of paramedics or ALS ambulances).[41]

VI.B. Implications & Extensions

VI.B.1 E911 and the Distribution of Intermediate Health Outcomes

Our theoretical framework suggests that the distribution of patient outcomes should be shifted by E911. Whereas Table 4 offers evidence that *average* intermediate health status is improved by E911 adoption, it provides no information about which patients experience the greatest improvement. For example, if intermediate health status deteriorates more quickly for sicker patients, the impact of E911 may be more pronounced for the more severe end of the health distribution. We address this issue in two ways. First, we examine (in unreported specifications) whether the impact of E911 varies with observable patient characteristics, such as age, sex, race, and insurance status.

[40] Of course, Basic may bring other benefits, such as in fire and police emergencies, where callers may be more sensitive to the ease of emergency reporting. However, when combined with centralization, Basic may slow down dispatch if it increases unfamiliarity by call-takers with remote geographic areas.
[41] Within our sample, only 75% of ambulances have paramedic attendants (who are required for pre-hospital defibrillation or emergency medicine administration), indicating that paramedics may be scarce. However, within our sample, EMD adoption does not increase in the likelihood of a paramedic on board.

We both split the sample according to these characteristics (performing separate regressions for each group), and examined specifications including interaction effects between patient characteristics and technology and EMD adoption. Perhaps surprisingly, no robust findings emerge from this analysis; the interaction effects tend to be imprecisely estimated, and the size and significance of any result varied according to the precise specification employed.

Second, Figure B provides a direct assessment of how E911 shifts the distribution of intermediate health status. The figure is constructed by selecting the subsample of patients living in counties adopting E911 during the sample period. The dotted line represents the CDF of HINDEX for patients observed prior to E911 adoption, while the dashed line represents the CDF for patients after E911 adoption in those same counties. Each of the mass points represents a common combination of raw health status indicators (recall that HINDEX aggregates the impact of four intermediate health status measures).

Figure B illustrates that the distribution of HINDEX improves according to first-order stochastic dominance after E911 adoption, reinforcing our regression results from Table 4. Notice further that the probability of extremely poor health is reduced after E911 adoption. The probability that HINDEX is greater than or equal to .275 falls from .062 to .049 after E911 adoption. Second, the fraction of patients who fall into the healthiest category, characterized by HINDEX less than or equal .014, increases from .737 to .785 following E911 adoption.

Figure B suggests that the impact of E911 is most dramatic on the most critical patients, a hypothesis reinforced by several robustness checks. First, though Figure B does not control for patient demographics, location variables or a time trend, their inclusion does not impact our findings.[42] As well, for each dimension of raw health status (examined in isolation), E911 adoption reduces the proportion of patients in the lowest category for that dimension.

VI.B.2 The Timing of the Impact of E911: Evidence for Post-Adoption Learning

We are also interested in the timing of the impact of E911, for at least two reasons. First, for robustness, we would like to check that the impact attributed to E911 does not

[42] For example, the difference between the two CDFs is very similar, but smoother, if we replace HINDEX with the difference between HINDEX and the predicted values of HINDEX from a regression similar to (4B-3) but excluding the E911 technology adoption variable.

begin to arise prior to adoption. Second, we would like to evaluate whether learning takes place, that is, whether counties improve their performance as a function of time since adoption. To address this issue, we estimate a regression similar to (4B-3) but include dummy variables for each of 9 quarters "prior to" and "since" adoption of E911. For simplicity, we do not estimate separate time-varying parameters for Basic or EMD (no trend is discernible for these variables).[43]

Figure C plots the predicted values of HINDEX for each time period before and after E911 adoption (all other variables are assumed to be at their mean values). The results are suggestive, though wide confidence intervals make us cautious in our interpretation.[44] The mortality predictions associated with quarters prior to adoption are higher than all but the first mortality predictions for quarters since adoption. Indeed, where all but one of the quarters prior to adoption are associated with a mortality rate higher than .029, all but the first quarter since adoption mortality rates are below .029. While there is no discernible trend prior to adoption, the mortality probability falls in each of the first four quarters after adoption. Figure C is consistent with the presence of learning-by-doing where, over time, call-takers and E911 managers master the new technology and dispatching becomes more synchronized with information provided by the address database. These findings reinforce our initial inference that E911 adoption is associated with increased cardiac emergency response productivity. If anything, the Table 4 coefficients may be conservative, because late-adopting counties may not have realized their full productivity gains by the end of 1996.

VI.B.3 911 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? And, if so, does ignoring interaction effects result in a biased analysis of the returns to IT or job design? Testing complementarity requires comparing the incremental returns to EMD for high and low levels of technology, where the incremental returns are measured as distinct contrast parameters. These contrast

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[43] Because adoption dates differ across counties, each time-since/prior to-adoption coefficient is estimated for a changing group of counties. For example, counties adopting in June, 1994, will not contribute to the "3 quarters prior to adoption" coefficient. Because our data is only for 1994 and 1996, counties will experience a "gap" for time-since/prior to-adoption periods occurring during 1995.

[44] These results are robust to several alternative specifications and intermediate health status measures.

parameters are identified by the assumptions of the fixed-effects model.[45]

Table 5 reports the results, where we relax (4B-3) by replacing the technology and EMD variables by five dummy variables for each of five separately identified 911 technology/EMD combinations (NO 911*NO EMD is the omitted category). Consistent with our earlier results, E911 (either with or without EMD) is necessary for a significant improvement in HINDEX (we reject equality with either NO 911 or BASIC 911).

We perform a number of tests about the interaction between 911 technology and EMD (including separate tests for complementarity between EMD adoption and (a) None → Basic adoption; (b) None → E911 adoption; (c) Basic → E911 adoption or (d) a joint test of restrictions implied by (a)–(c)).[46] In contrast to theories emphasizing complementarity between IT and skill-oriented job design (or theories focusing on the de-skilling aspects of computerization), we cannot reject the hypothesis of no interaction effects between 911 technology and EMD. Of course, the benefits from EMD may be realized after ambulance arrival; however, we could find no evidence of complementarity for short-term mortality. Thus, while our findings concerning the impact of E911 are robust to accounting for interactions with EMD, accounting for this interaction does not appear to be critical for assessing the impact of IT on emergency health care outcomes.

VI.B.4 Nature of E911 Technology Diffusion

A central theoretical prediction relating to technology diffusion is that the sequence of adoption reflects the declining marginal productivity of adoption (Griliches, 1957; Rogers, 1983). If tue, the measured productivity benefits associated with adopters may be upward-biased as an estimate of the benefit for an average *potential* adopter. While Section V presents some evidence that our sample period captures adoption by "average" counties, this section compares the productivity of adopting counties, before and after adoption, to the productivity of those adopting before and after the sample period.

We divide the sample into four groups, according to their E911 adoption status: pre-1994 adopters, within-sample E911 adopters prior to adoption, within-sample E911

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[45] Identification of the interaction effect exploits both cross-sectional and time-series variation. Each county experiences only two or three systems, while complementarity is defined in terms of the returns to four distinct systems. If unobserved incremental returns to 911 systems are independent of the switching regime and date, then, under (A2), comparing estimated contrast parameters across counties is valid.

[46] We also conducted the specification test suggested in Section III.C, allowing each type of switch to have a separate coefficient, testing the restrictions implied by (A2). We cannot reject the hypothesis that these restrictions are valid, and so we maintain (A2) for the analysis.

adopters after adoption, and post-1996 adopters. We estimate a regression similar to (4B-3), except that we include a dummy variable for each of these groups (note that we thus exclude location-specific fixed effects but include other control variables). We then estimate a predicted HINDEX value for each group, using the sample means of all variables except for the technology adoption status variable, and plot these in Figure D. The difference between pre-adoption and post-adoption predicted values for within-sample adopters is simply an estimate of the impact of E911 on mortality (i.e., .036 - .033 = .003; the estimate is slightly different than Table 4B because the specification does not include MCD fixed effects). We apply this estimate to counties not adopting during the sample period, to illustrate the *predicted* levels of HINDEX for pre-sample adopters in the absence of adoption and post-sample adopters after E911 adoption, respectively.

Several things stand out. Pre-1994 E911 adopters have a higher HINDEX than within-sample adopters after adoption. If E911 does have positive returns, then the early adopter population is associated with particularly poor health outcomes. As well, within-sample E911 adopters have the *highest* mortality probabilities of all groups prior to E911 adoption, but, after adoption, "leapfrog" over pre-sample adopters to a point just above the post-sample adopter group. Finally, counties not adopting E911 by the end of 1996 have the lowest probability of mortality; if E911 confers benefits, adoption by these counties would shift their outcomes to a new population frontier.

These results shed light on the salience of alternative theories of technological diffusion. The within-sample adopters are neither associated with poor health status both prior to and after adoption (which would be consistent with selectivity bias or mean reversion), nor do within-sample adopters experience superior productivity both before and after adoption (which would be consistent with a positive correlation between E911 adoption during the sample period and superior health care infrastructure). Indeed, our results are consistent with a simple adoption story whereby early adopters tend to have low levels of productivity (i.e. high mortality), and so can have the greatest incremental improvement in terms of lowering this mortality probability. Under that interpretation, our estimates of the impact of E911 would be conservative; if early adopters experience higher incremental returns, these returns would accrue to the large fraction (over 50%) of the sample population who had E911 prior to 1994.[47]

[47] We have explored several additional extensions to test for selectivity, including interaction terms between E911 adoption and various county characteristics (e.g., population, income, density, and the level

VI.B.5 Alternative Time Trends, Correlated Observations, and Sample Limitations

Our final extensions offer additional robustness checks evaluating the sensitivity of the differences-in-differences estimation strategy to the assumptions of the fixed effects model and our sampling scheme. Table 6 reports a subset of these robustness checks; we also discuss ancillary (unreported) results that shed further light on our main findings.

First, we relax the assumption that all counties experience a common time trend. Heterogeneity in the trend experienced by different populations is particularly important if one is concerned about the potential for the selectivity of adopters (Blundell and MaCurdy, 1999). For example, observed adopters may simply be associated with a higher overall time trend. We address this concern by evaluating multiple alternative time trends. For example, in an (unreported) specification, a separate time trend for "high-density" and "low-density" counties is included; the core results remain unchanged, and no significant difference exists between the group-specific time trends. Similar results obtain for time trends based on population, per capita income, and other county-level and MCD-level demographics. In (6-1), the time trend is allowed to depend on each county's initial technology level, allowing heterogeneity across counties based on their pre-1994 adoption behavior. There is no change to the E911 results, and no significant difference between the three time trends. The result is similar if we allow the time trends to depend on the county's final technology level.

We further consider the assumption of independence within each county over time. While our results include MCD fixed effects, and we adjust all standard errors for correlation within county-quarter groups, it is important to consider the sensitivity of differences-in-differences results to the possibility of location-specific serial correlation over longer time horizons (Bertrand et al, 2001), perhaps from persistent shocks to 911 center productivity. (6-2) reports a specification where the standard errors are adjusted for correlation within counties over the entire sample period; the coefficients remain significant and of similar magnitude. The small changes to the calculated standard errors suggest a low level of location-specific serial correlation in these data. This is not too surprising, as our specification includes controls for many potential sources of correlation among observations, and our interviews and survey suggest that most 911 systems were

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of HINDEX in a county in the first quarter of 1994). There is no consistent evidence for a robust interaction effect that would suggest substantial selectivity in our sample.

relatively stable but for the adoption of 911 technology and EMD.[48]

Finally, we consider alternative sampling schemes. First, we consider a narrower cardiac emergency definition, as defined by the ICD9 codes assigned to patients at the admitting hospital. So far, our sample is defined according to a generous definition of cardiac emergency (3-digit ICD9 codes from 400-459), while (6-3) restricts attention to 3-digit ICD codes from 400-429, focusing only on more severe cardiac conditions. Though eliminating nearly a quarter of the sample, the findings remain consistent with our earlier results (though the coefficient test of BASIC = E911 is only rejected at the 10% level). While the core findings hold with even stricter sample restrictions, the estimates become noisier as the sample size is further reduced.. In (7-4), we present a final sampling check, excluding highly populated and particularly high mortality counties. This allows us to test in more detail how the results depend on demographic characteristics or the pre-existing health distribution of adopting counties. As before, the results are similar in this specification.

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

Our final empirical exercises examine the effect of technology and EMD on patient outcomes after hospital admission, including the effect on the mortality hazard rate and the level of average hospital costs. These complement the prior analysis in two ways. First, we are able to investigate whether patient welfare improves as a result of E911 adoption. Such a finding provides direct evidence that early intervention has medical benefits. One alternative hypothesis would be that it is possible to compensate for late ambulance arrival by providing more aggressive treatment; in that case, mortality would not be affected, but average medical costs would fall after adoption. Second, exploring more traditional health care outcome measures highlights the role played by the nuanced intermediate health status measures. While mortality or costs are more closely tied to long-term patient welfare, these measures are less closely tied to the impact of E911. We expect that the impact of E911 may be more difficult to discern in hospital outcomes, given the potential for medical intervention after ambulance arrival, as well as the inherent uncertainty associated with mortality.

Before proceeding, we emphasize that the structure of the data leads us interpret our

[48] We have also calculated county-month averages for each of our outcome measures, repeating the analysis with the county-month as the unit of observation. The main findings remain significant.

outcomes results cautiously. We do not observe comprehensive medical records for patients, but instead observe only hospital discharge records for the first hospital to which the patient is admitted after the emergency incident.

We begin with an examination of how technology and EMD impact the hazard rate of mortality. For each patient, we observe both the time and type of patient discharge. Until this discharge, we can evaluate the patient's status as a function of the number of hours since initial ambulance emergency intervention. As well, at the time of discharge, we observe whether the patient is released, transferred to another hospital, or dead. Though we believe that release to home soon after the emergency incident is a positive outcome closely associated with longer-term survival, transfer to another hospital soon after the emergency incident is associated with more ambiguity. As well, the interpretation of all outcomes is more ambiguous for discharges long after the emergency incident (e.g., after a long initial hospital stay, release to home may be associated with a short home stay followed by readmission or the need for surgery). Thus, we consider short-term outcomes, occurring up to 6 or 48 hours after the initial emergency incident.

Given this data structure, it is natural to consider a hazard function for hospital discharges. Given a time frame, τ^F, over which we consider outcomes, we distinguish between observations associated with (a) a death outcome at hour τ, prior to τ^F; (b) a transfer prior to τ^F (treated as right-censored); (c) release to home prior to τ^F (treated as survival until τ^F)[49] or (c) survival and no discharge until τ^F. We present two Cox proportional hazard models (see, e.g., Cox (1972)) in Table 7 to highlight the main results. Formally, we estimate the following discrete-time hazard model, following the notation in (2), and where l_k is the identity of the hospital where patient *k* is admitted:

$$\begin{aligned}&\Pr(\text{Patient}(i,j,k,t)\text{ dies at hour }\tau \mid \text{Alive at hour }\tau-1,\ \mathbf{s}_i^t,\mathbf{x}_k,\mathbf{z}_j^t,l_k)\\ &\quad\equiv H(\tau\mid \mathbf{s}_i^t,\mathbf{x}_k,\mathbf{z}_j^t,l_k)=H_{j,l_k}(\tau)\cdot\exp\left\{q_t+E911_{i,t}(\alpha_{E911}-\alpha_{\text{NOT }E911})+\mathbf{x}_k\,\boldsymbol{\beta}+\mathbf{z}_j^t\boldsymbol{\gamma}\right\}\end{aligned} \tag{3}$$

We account for the existence of both patient heterogeneity, as well as heterogeneity across hospitals, by stratifying by the patient's hospital and MCD, that is, by allowing the baseline hazard function, $H_{j,l}(\tau)$, to vary by hospital and MCD (no assumptions are required on the shape of each $H_{j,l}(\tau)$). With this specification, the coefficients are

[49] Unlike cancer or some other terminal illnesses, patients are rarely sent "home to die" following an acute cardiac incident. A patient at risk of imminent death would typically be kept in the hospital. Our results are not sensitive to this assumption.

identified from variation within the hospital/MCD pair. As well, we include the control variables incorporated into earlier models, except for the patient billing zip code demographics (which lack sufficient variation within a hospital/MCD pair).

The results are presented in the first two columns of Table 7; we report the Cox proportional hazard coefficients (i.e., $\tilde{\beta} = \exp\{\beta\}$ is the proportional change in the hazard rate, so that a coefficient of 1 is associated with no change in the hazard). For both the 6-hour and 48-hour hazard model, E911 is associated with a significant reduction in the hazard. In the 6-hour specification, the mortality hazard is reduced by over 60% after E911 adoption (significant at the 5% level), while in the 48-hour specification, we find over a 35% reduction in the hazard (significant at the 10% level). These results are robust to the particular functional form, the inclusion or exclusion of control variables, and the form of stratification. To interpret the estimates, observe that they imply that the cumulative probability of death within 6 hours falls by .005 (relative to a mean of .008), while the probability of death within 48 hours falls by .012 (relative to a mean of .035). Similar to our earlier results, we could find no significant association between the mortality hazard and EMD adoption.

Both (7-1) and (7-2) assign No 911 and Basic into a single technology grouping. We present this specification because the effect of Basic is imprecisely estimated, and its sign and magnitude are sensitive to specification (e.g., the estimate varies widely with whether the stratification included hospital effects). Across all specifications, however, E911 is associated with a lower hazard rate than the joint impact of No 911 and Basic.

Consider the relationship between these results and our results about HINDEX (recall that E911 improved the average HINDEX by .04). As discussed in Section III, the relationship between improvement measured at the time of ambulance arrival and improvement in actual mortality depends on the importance of timeliness of medical intervention. Consistent with the clinical literature, our finding that the effect of E911 on mortality is greater than its effect on HINDEX suggests that follow-on medical interventions amplify the impact of faster response times.

Finally, consider the impact of technology and EMD on realized health care expenditures. As mentioned earlier, one potential benefit to E911 might be to lower costs, by allowing for earlier (and potentially cheaper) medical interventions. In (7-3), we consider a simple patient cost regression. Similar to our mortality analysis, we include fixed effects for each MCD-hospital combination observed in the dataset. As such, our results are identified by differences in the average cost of care after technology adoption among patients whose incident occurs in the same narrow geographic area and who receive treatment at the same hospital (our results are robust, however, to alternative control structures).[50] The results are suggestive. E911 adoption is associated with approximately a 16% reduction in average total expenditures (average expenditures are $6,400, when adjusted by Medicare cost-to-charge ratios); however, the adoption of BASIC is associated with a similar decrease in costs. In other words, in contrast to the rest of the analysis, where we can differentiate the benefits of E911 from Basic, Basic and E911 seem to have similar effects on average hospital costs.

Throughout the analysis, we do not find benefits to EMD. Although it may not be surprising that EMD has little effect on intermediate health status, our discussion suggests hospital outcome measures might have provided a better estimates of the benefits of EMD. However, we find no significant benefit to EMD (the point estimates tend to be negative). We thus 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.

VII. Implications and Conclusions

The main contribution of this paper is to document that the adoption of E911 improves the timeliness of emergency responses, as measured by patient health status at the time of ambulance arrival. We also provide evidence that this timeliness improves patient welfare. To evaluate E911 adoption from the perspective of social welfare, we must compare the costs and benefits of adoption. Several difficulties arise in performing such a comparison. First, 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 20% of all emergencies, and, at least in one Pennsylvania county which maintains statistics, ambulance incidents make up just 33% of all dispatched calls (a little over 50% are police, and the remainder are associated with fire).

[50] Because the dependent variable is the log of total charges, and the fixed effects are at a level finer than each hospital, adjusting by the Medicare cost-to-charge ratio has no impact on the regression results..

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. Based on our interviews and industry sources, we estimate initial adoption costs for a system (starting from No 911) at approximately \$2 million, with about \$400,000 incremental operating costs.[51] The incremental costs relative to Basic are smaller. Given that the E911 equipment is likely to be operational and effective for at least five years, an estimate of the annualized cost of adoption is approximately \$800,000. Now consider our estimates of the impact of E911 on short-term mortality. In Section VI.C, we estimated that the cumulative effect of E911 is -.005 for 6-hour mortality and -.012 for 48-hour mortality. Finally, the expected number of cardiac incidents in an average county (with population 273,000) is estimated to be 304. If we use a value of \$450,000 per life saved,[52] then using the conservative estimate -.005, the estimated benefits are equal to \$684,000. In other words, the benefits arising from a category comprising less than 10% of emergency calls covers at least 85% of the cost of adoption. Thus, our evidence suggests that E911 adoption results in a substantial increase in social welfare for an average county.

In conclusion, this paper highlights a general issue about productivity measurement in the service sector. Rather than attempt to evaluate the gains from IT by aggregating across a wide variety of heterogeneous establishments and applications of IT, our approach is to identify a specific application and to tailor both the measurement of IT and the productivity analysis to fit the application. While this approach may not be feasible for every application, our analysis provides some perspective about the types of output measures (e.g., measures responsive to timeliness) that may form the basis for more consistent productivity measurement in the service sector. The development and evaluation of such measures seems a promising area for further research.

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[51] A No 911 system shares expenses over a large number of agencies, where each agency employs additional personnel to staff telephones. Thus, we do not assume that a No 911 system is "free."

[52] Of course, this value is arbitrary, as we do not know the long-term life expectancy of the patient sample we consider. The short-term mortality rate in our sample is about half as high as that from samples that include only AMI patients, but the patients whose lives are saved by E911 are probably similar in health to AMI patients (recall Figure B). Cutler et al (1999) show that in 1994, AMI survivors had a life expectancy of 6 years, and they use a quality weight of .74 relative to a weight of 1 for perfect health. If we value a year of life in perfect health at \$100,000, then the value of a life saved is \$444,000.

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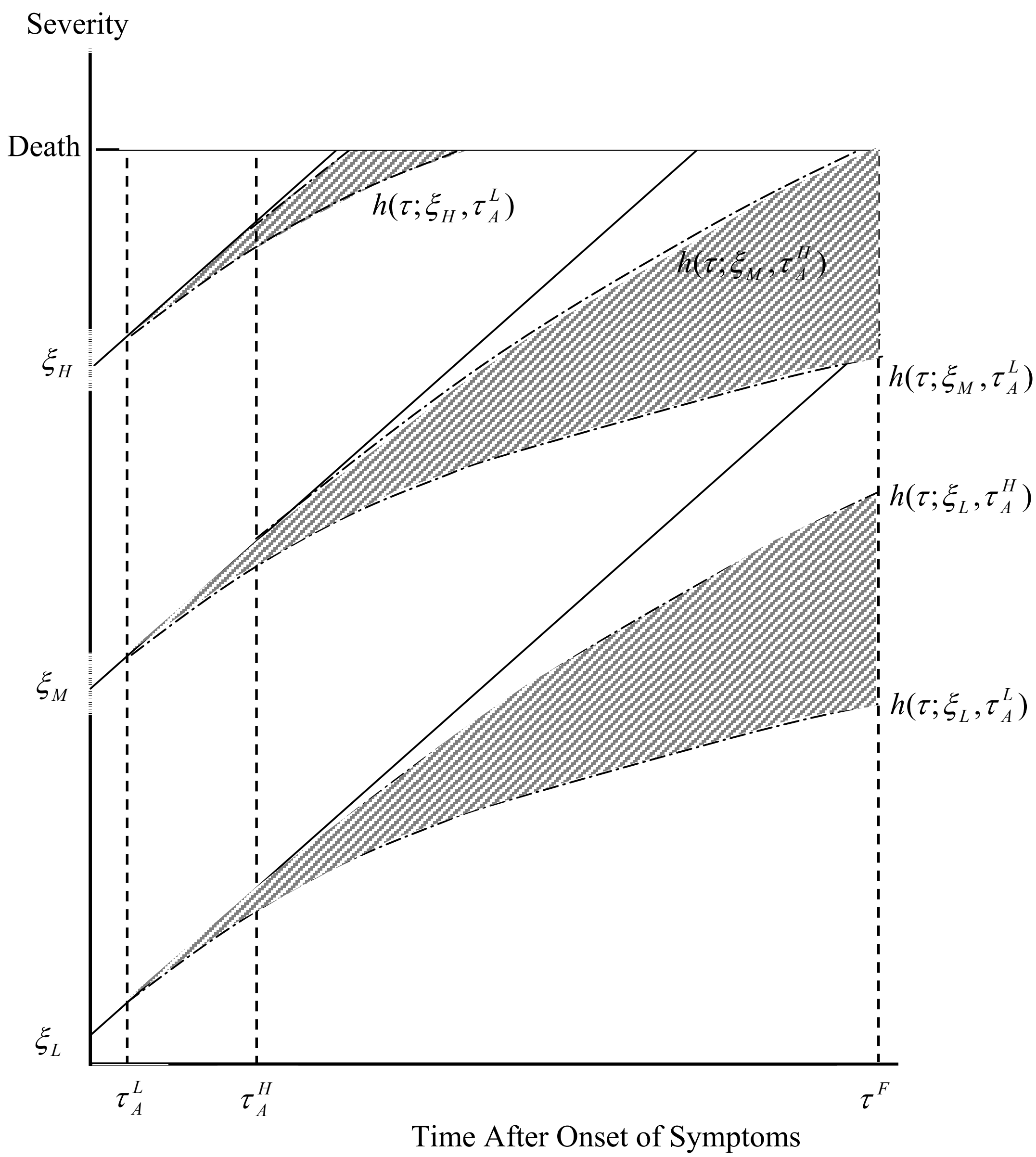
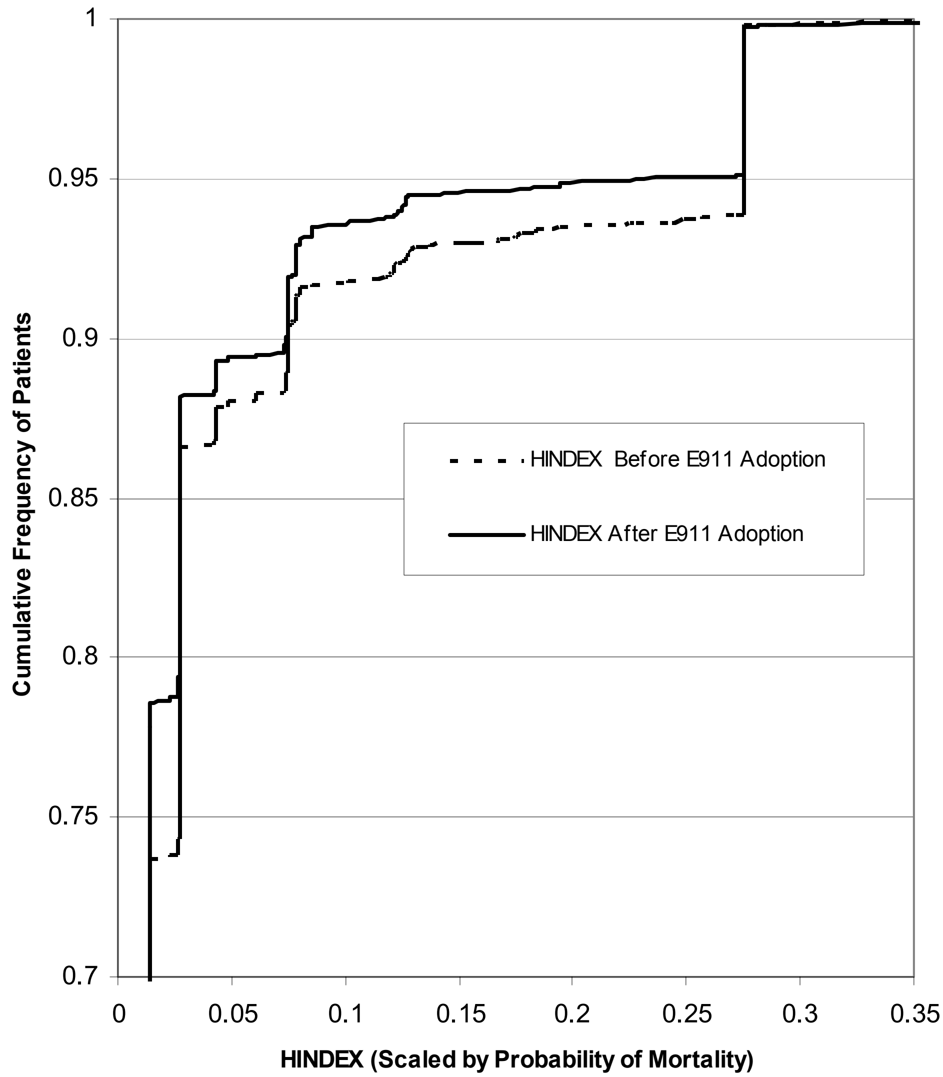
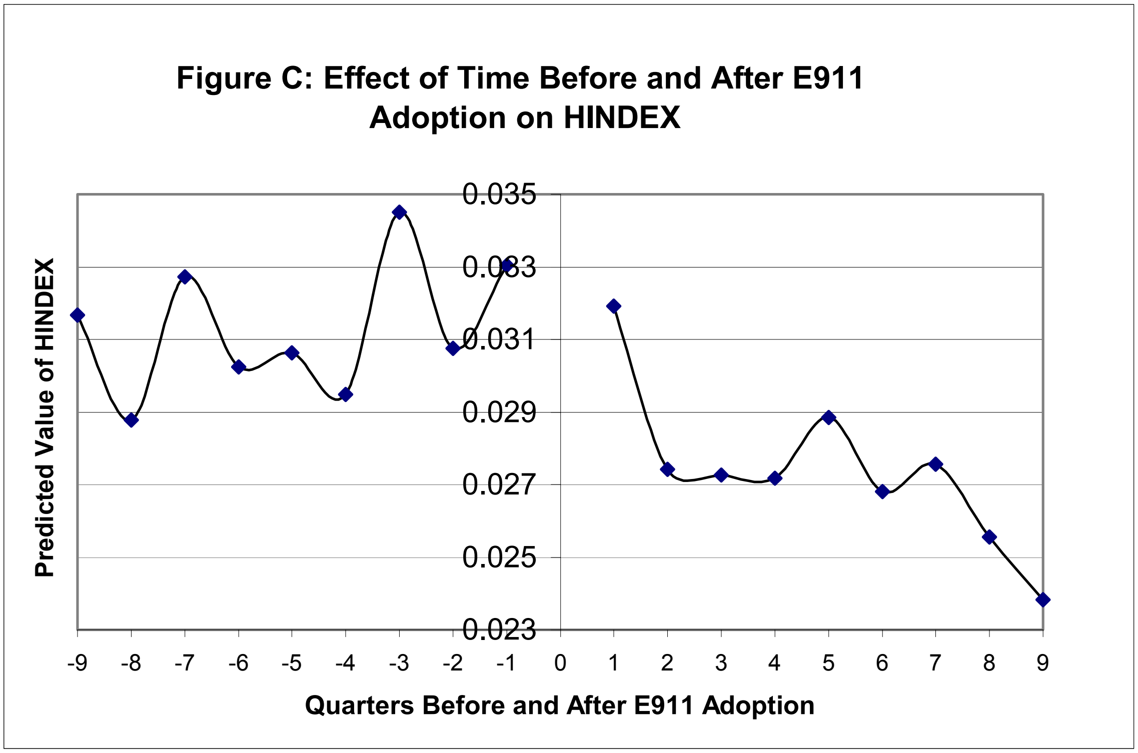


Figure A: The Health Status Production Function

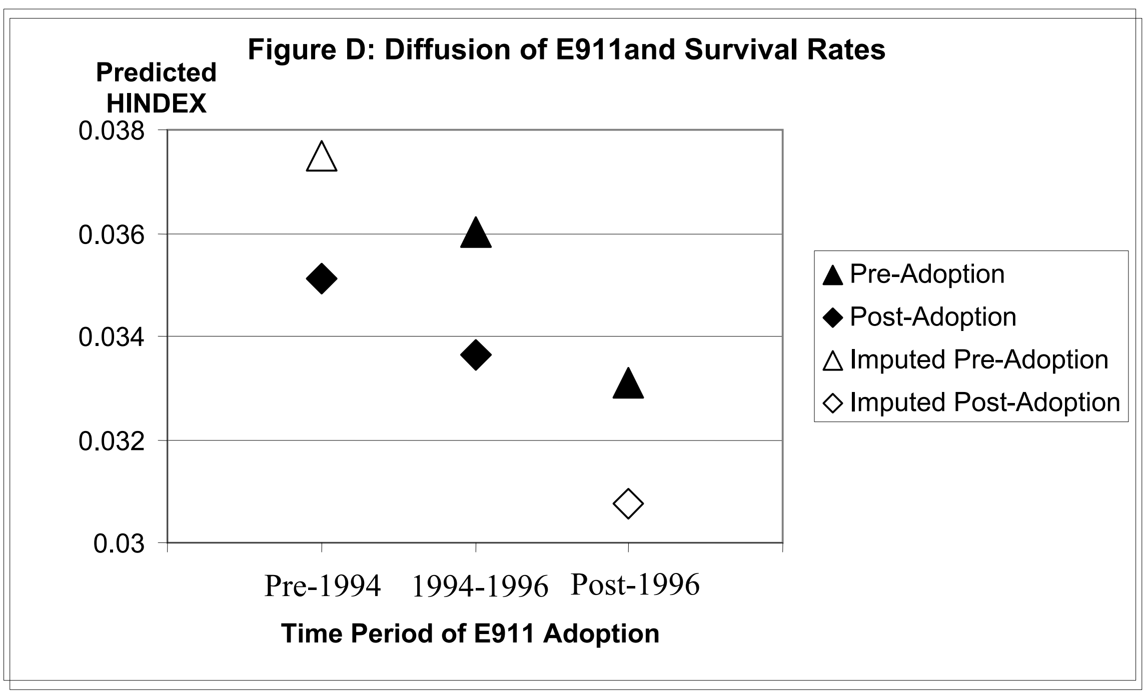
Figure B: Cumulative Distribution of HINDEX Before and After E911 Adoption



Notes: This figure includes only incidents that occurred in counties that adopted E911 during 1994-1996, and incidents are assigned a group based on whether they occurred before or after E911 adoption. The cumulative distribution functions are approximately 0 for the range excluded from the figure.



Notes: The coefficients are derived from a regression of LL(HINDEX) on dummy variables for the quarters before and after adoption, as well as the control variables used in Table 4B-3.



Notes: The points on the figure represent the predicted values of HINDEX, calculated from a regression that is the same as the one reported in Table 4B-3, except that No 911 and Basic are pooled into a single category, we omit MCD fixed effects, and we include dummy variables for the groups of counties and time periods illustrated in the graph.

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 at Scene	PA EMS
RESPIRATION	Respiration Rate	Respiration Rate as measured at Scene	
PULSE	Pulse Rate	Pulse Rate as measured at Scene	
GLASGOW	Glasgow Coma Score	Score from 3-15 indicating patient alertness/ responsiveness; higher scores indicate greater alertness	
48 HR MORTALITY	48 Hour Mortality Dummy	Discharged Dead at < 48 Hours	
6 HR MORTALITY	6 Hour Mortality Dummy	Discharged Dead at < 6 Hours	
TOTAL COSTS	Total Costs	Total Hospital Charges, adjusted by hospital-specific Medicare cost-to-charge ratio	PA EMS; Medicare Cost Reports
CONSTRUCTED PATIENT HEALTH STATUS MEASURES			
HIGH RISK BP	High Risk Blood Pressure Dummy	HIGH RISK BP = 1 if BLOOD PRESSURE < 90	Authors' Calculation
HIGH RISK PULSE	High Risk Pulse Rate Dummy	HIGH RISK PULSE = 1 if PULSE <= 40	
HINDEX	Calculated Health Index	Predicted values of 48 HR MORTALITY probit on Blood Pressure, Respiration, Pulse, and Glasgow categories (see Appendix A)	
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, defined as countywide 9-1-1 caller availability	
E911	Enhanced 911 Dummy	"Enhanced 911" in County on INCIDENT DATE, defined as adoption of ALI technology and ALI availability for > 50% of addresses in county	
EMD	Emergency Medical Dispatch System Dummy	Emergency Dispatch System in County on INCIDENT DATE, defined as mandatory EMD training and EMD protocol in use	
INCIDENT TIMING			
QUARTER DUMMIES	Quarterly Dummies	Eight Quarterly Dummies Based on INCIDENT DATE	PA EMS
HOUR DUMMIES	Incident Time-of-Day Dummies	Eight Dummies for Incident Time-of-Day; Groupings Based on Continuous Periods of Comparable Call Volume	
PATIENT DEMOGRAPHIC AND HEALTH INSURANCE CHARACTERISTICS			
MALE	Male Sex Dummy	Male Sex Dummy	PA EMS
AGE	Patient Age	Patient Age	
MEDICARE	Medicare Dummy	MEDICARE = 1 if Primary Insurance is Medicare	
MEDICAID	Medicaid Dummy	MEDICAID = 1 if Primary Insurance is Medicaid	
PRIVATE	Private Health Insurance Dummy	PRIVATE = 1 if Primary Insurance is Blue Cross, Private HMO, or Other Private Health Insurance	
SELF_PAY	Self-Pay Dummy	SELF_PAY = 1 if No Insurance	
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	Percentage Black In Zip Code Population (1990 Census)	
ZIP % FOREIGN	Percentage Foreign-Born	Percentage Foreign-Born in Population (1990 Census)	
ZIP % High School or Better	Percentage Completed High School Education or Better	Percentage Completed High School Education or Better (1990 Census)	
PATIENT INCIDENT PRE-HOSPITAL INFRASTRUCTURE – MCD-LEVEL (M_*)			
M QUARTERLY AMBULANCES	Total Ambulances in INCIDENT Quarter	Total Distinct Ambulances in MCD in INCIDENT Quarter	PA EMS
M ALS SHARE	ALS Share of QUARTERLY AMBULANCES	Total Distinct ALS Ambulances in MCD in INCIDENT Quarter / QUARTERLY AMBULANCES	
M PRECIPITATION	Daily Precipitation Dummy	PRECIPITATION = 1 if Precipitation on INCIDENT DATE >.1 inches	National Climatic Data Center
M SNOWFALL	Daily Snowfall Dummy	SNOWFALL = 1 if Snowfall on INCIDENT DATE > .5 inches	
M SNOW DEPTH	Snow Depth Dummy	SNOW DEPTH = 1 if Snow Depth on INCIDENT DATE > 12 inches	
M MAX TEMP	Daily Maximum Temperature	MAX TEMP= 1 if Max Temp Reading on INCIDENT DATE > 90 F	
M MIN TEMP	Daily Minimum Temperature	MIN TEMP =1 if Min Temp Reading on INCIDENT DATE < 0 F	
PATIENT INCIDENT LOCATION DEMOGRAPHICS – COUNTY-LEVEL (C_*)			
C POPULATION	County Population	County Population (1990 Census)	US Census Bureau
C DENSITY	County Population Density	County Population / County Square Mileage (1990 Census)	
C PERCAP INCOME	Per Capita Income	County Per Capita Income (1990 Census)	
C HOSPITALS	Total Hospitals in County	Total Distinct Hospitals in County	AHA Survey
C MONTHLY PATIENTS	Total Emergency Patients in County in Given Month	Total Emergency Patients in County in INCIDENT Month	PA EMS

* 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		MEAN	STANDARD DEVIATION
RAW MEASURES OF PATIENT HEALTH STATUS AND EXPENDITURES			
BLOOD PRESSURE		137.147	49.467
RESPIRATION		21.404	8.113
PULSE		85.815	34.608
GLASGOW		14.112	2.943
48 HR MORTALITY		0.035	0.183
6 HR MORTALITY		0.008	0.090
TOTAL COSTS		6400.319	7907.794
CONSTRUCTED PATIENT HEALTH STATUS MEASURES			
HIGH RISK BP		0.103	0.304
HIGH RISK PULSE		0.065	0.247
COUNTY-LEVEL EMERGENCY RESPONSE SYTEM MEASURES			
NO 911		0.148	0.355
BASIC 911		0.172	0.377
E911		0.679	0.467
EMD		0.490	0.500
NON-HEALTH STATUS PATIENT CHARACTERISTICS			
MALE		0.512	0.500
AGE		70.221	12.970
MEDICARE		0.676	0.468
MEDICAID		0.047	0.212
PRIVATE		0.205	0.404
SELF_PAY		0.009	0.092
PATIENT & INCIDENT LOCATION DEMOGRAPHICS			
PATIENT BILLING ADDRESS ZIP CODE DEMOGRAPHICS (Z_*)			
ZIP	PERCAP INCOME	13656.460	4629.954
ZIP	% BLACK	0.042	0.105
ZIP	% FOREIGN	0.024	0.022
ZIP	% High School or Better	0.177	0.042
MCD-LEVEL INCIDENT LOCATION PRE-HOSPITAL INFRASTRUCTURE – (M_*)			
M	QUARTERLY AMBULANCES	5.158	4.147
M	ALS SHARE	0.758	0.302
M	PRECIPITATION	0.251	0.434
M	SNOWFALL	0.056	0.230
M	SNOW DEPTH	0.070	0.256
M	MAX. TEMPERATURE	0.020	0.139
M	MIN. TEMPERATURE	0.027	0.164
COUNTY-LEVEL INCIDENT LOCATION DEMOGRAPHICS (C_*)			
C	POPULATION	273136.900	192711.300
C	DENSITY	579.971	687.654
C	PERCAP INCOME	18244.870	4042.793
C	TOTAL HOSPITALS	4.209	2.162
C	MONTHLY PATIENTS	307.268	51.537

TABLE 3
COUNTY CHARACTERISTICS
BY TYPE OF SWITCHING BEHAVIOR

	REGIME						
	NON-SWITCHERS				SWITCHERS		
	No 911	**Basic 911**	**Pre-1992 E911 Adopter**	**1992-1993 E911 Adopter**	**None to Basic**	**None to E911**	**Basic to E911**
	AVERAGE COUNTY CHARACTERISTICS BY REGIME						
# COUNTIES	5	6	4	19	8	9	14
COUNTY POPULATION	128983.20 (150763.50)	68393.83 (59513.80)	187883.80 (183492.20)	233823.80 (195661.00)	53841.13 (41709.36)	92705.33 (59126.33)	113849.60 (111117.20)
COUNTY PER CAPITA INCOME	14881.40 (2501.56)	15563.83 (1247.87)	16511.75 (3560.91)	17824.95 (4159.73)	16474.50 (1496.24)	14966.11 (1529.32)	15521.57 (1972.43)
COUNTY DENSITY	227.80 (289.88)	99.17 (75.42)	209.75 (211.83)	517.68 (692.83)	74.63 (49.60)	148.78 (76.51)	172.57 (149.64)
PATIENT AGE	68.97 (2.73)	68.59 (2.35)	70.86 (2.19)	70.00 (1.47)	68.38 (3.55)	71.03 (1.49)	69.74 (1.86)
48 HR MORTALITY	0.029 (0.013)	0.025 (0.021)	0.048 (0.023)	0.045 (0.021)	0.021 (0.017)	0.030 (0.008)	0.024 (0.017)

TABLE 4A
IMPACT OF EMS VARIABLES ON HIGH RISK BLOOD PRESSURE*

	(4A-1) Emergency Medical System (EMS) Variables and Quarterly Dummies			**(4A-2)** EMS Variables, Quarterly Dummies & County Fixed Effects			**(4A-3)** EMS Variables, Quarterly Dummies & MCD Fixed Effects		
DEPENDENT VAR.				HIGH RISK BP					
EMERGENCY RESPONSE SYSTEM VARIABLES									
BASIC		-0.004 (0.010)			-0.008 (0.012)			-0.002 (0.012)	
E911		0.006 (0.009)			**-0.041** **(0.012)**			**-0.045** **(0.013)**	
EMD		0.005 (0.006)			0.009 (0.008)			0.011 (0.010)	
Parametric Restrictions	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	1	1.90	0.169	**1**	**7.72**	**0.006**	**1**	**11.89**	**0.0006**
QUARTERLY DUMMIES (Q1 1994 is Excluded Quarter)									
Q2 1994		0.007 (0.010)			0.007 (0.006)			0.008 (0.007)	
Q3 1994		0.006 (0.011)			-0.001 (0.007)			0.006 (0.008)	
Q4 1994		0.014 (0.011)			0.008 (0.007)			0.013 (0.008)	
Q1 1996		-0.002 (0.010)			0.002 (0.007)			0.004 (0.008)	
Q2 1996		0.010 (0.010)			**0.016** **(0.008)**			*0.017* *(0.008)*	
Q3 1996		0.005 (0.012)			0.009 (0.010)			0.011 (0.011)	
Q4 1996		*0.018* *(0.011)*			**0.027** **(0.008)**			**0.028** **(0.009)**	
R-Squared		0.001			0.017			0.129	
Adjusted R-Squared		0.001			0.014			0.031	
Observations		19746			19746			19746	

* Robust standard errors, adjusted for clustering by county-quarter, are in parentheses.

TABLE 4B
IMPACT OF EMS VARIABLES ON ALTERNATIVE INTERMEDIATE HEALTH STATUS MEASURES WITH DETAILED PATIENT & LOCATION CONTROLS*

	(4B-1) EMS Variables, All Control Variables and MCD Fixed Effects			**(4B-2)** EMS Variables, All Control Variables and MCD Fixed Effects			**(4B-3)** EMS Variables, All Control Variables and MCD Fixed Effects		
DEPENDENT VAR.	HIGH RISK BP			HIGH RISK PULSE			LL HINDEX		
EMERGENCY RESPONSE SYSTEM VARIABLES									
BASIC	-0.005 (0.012)			-0.010 (0.011)			-0.019 (0.036)		
E911	**-0.043** **(0.012)**			**-0.035** **(0.012)**			**-0.118** **(0.038)**		
EMD	0.009 (0.010)			0.007 (0.009)			0.019 (0.029)		
Parametric Restrictions	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	**1**	**10.54**	**0.001**	**1**	**6.55**	**0.011**	**1**	**8.43**	**0.004**
CONTROL VARIABLES									
PATIENT DEMOGRAPHIC & INSURANCE CHARACTERISTICS									
MALE	**0.027** **(0.005)**			**0.017** **(0.004)**			**0.071** **(0.014)**		
AGE 46-55	-0.012 (0.014)			0.002 (0.010)			-0.001 (0.037)		
AGE 56-65	**0.027** **(0.013)**			*0.017* *(0.010)*			**0.108** **(0.034)**		
AGE 66-75	**0.028** **(0.013)**			**0.034** **(0.010)**			**0.150** **(0.035)**		
AGE 75+	0.009 (0.013)			0.011 (0.009)			**0.108** **(0.033)**		
MEDICAID	0.006 (0.012)			-0.009 (0.009)			0.004 (0.035)		
PRIVATE	0.010 (0.008)			0.008 (0.007)			0.005 (0.023)		
SELF-PAY	0.052 (0.031)			**0.064** **(0.025)**			*0.156* *(0.083)*		
OTHER INSURANCE	0.001 (0.011)			0.005 (0.009)			-0.005 (0.033)		
PATIENT BILLING ADDRESS ZIP CODE CHARACTERISTICS									
Z_BLACK	**0.152** **(0.043)**			**0.119** **(0.033)**			**0.444** **(0.121)**		
Z_FOREIGN	0.105 (0.186)			0.136 (0.159)			0.349 (0.556)		
L Z_PERCAP INCOME	0.019 (0.020)			0.014 (0.019)			0.056 (0.059)		
Z_%HIGH SCHOOL+	-0.061 (0.133)			-0.054 (0.119)			-0.163 (0.387)		
TIME-VARYING INCIDENT LOCATION CHARACTERISTICS									
MCD LEVEL									
L M_QUARTERLY AMBULANCES	-0.004 (0.006)			-0.001 (0.005)			-0.008 (0.018)		
M_ALS SHARE	-0.015 (0.017)			-0.008 (0.014)			-0.036 (0.051)		
SNOWFALL	0.003 (0.011)			-0.004 (0.008)			-0.021 (0.029)		

SNOW DEPTH	0.001 (0.008)			0.008 (0.007)			0.030 (0.024)		
PRECIPITATION	-0.005 (0.005)			-0.005 (0.004)			-0.020 (0.017)		
MAX TEMP	0.013 (0.018)			0.002 (0.015)			0.027 (0.047)		
MIN TEMP	0.026 (0.017)			0.019 (0.015)			0.057 (0.051)		
COUNTY LEVEL									
L C_MONTHLY PATIENTS	0.009 (0.008)			0.001 (0.006)			0.013 (0.022)		
Constant	0.225 (0.204)			0.246 (0.181)			**-3.399** **(0.605)**		
INCIDENT TIMING									
Joint Significance Tests	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
QUARTERLY DUMMIES	**7**	**2.91**	**0.005**	**7**	**1.80**	**0.082**	**7**	**2.11**	**0.040**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**13.30**	**0.000**	**8**	**13.20**	**0.000**	**8**	**8.32**	**0.000**
R-Squared	0.141			0.152			0.151		
Adj. R-Squared	0.042			0.055			0.054		
Observations	19746			19746			19746		
# Obs - # Parameters	17709			17709			17709		

* Robust standard errors, adjusted for clustering by county-quarter, are in parentheses.

TABLE 5
IMPACT OF EMS VARIABLES ON INTERMEDIATE HEALTH STATUS: INTERACTION EFFECTS*

EMS Interactions Including Patient and Incident Location Characteristics (MCD FE)			
Dependent Variable = LL HINDEX			
EMERGENCY RESPONSE SYSTEM VARIABLES			
BASIC* NO EMD		-0.041 (0.041)	
E911* NO EMD		**-0.144** **(0.044)**	
NO 911* EMD		-0.061 (0.071)	
BASIC*EMD		-0.018 (0.064)	
E911* EMD		**-0.116** **(0.042)**	
Parametric Restrictions	#Restrict	F-stat	p-value
PRACTICE TESTS			
NO 911 = BASIC	2	0.65	0.522
NO 911 = E911	**2**	**5.57**	**0.004**
BASIC = E911	**2**	**4.52**	**0.011**
EMD = NO EMD	3	0.58	0.631
INTERACTION TESTS			
EMD*BASIC – EMD*NO911 – NOEMD*BASIC = 0	1	0.97	0.325
EMD*E911 – NOEMD*E911 – EMD*NO911 = 0	1	1.34	0.247
(EMD*E911 + NOEMD*BASIC) – NOEMD*E911 – EMD*BASIC = 0	1	0.01	0.934
JOINT TEST OF PREVIOUS THREE	2	0.71	0.490
CONTROL VARIABLES			
QUARTERLY DUMMIES	**7**	**2.07**	**0.043**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**8.30**	**0.000**
PATIENT CHARACTERISTICS	**14**	**7.50**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	8	0.83	0.576
R-Squared		0.151	
Adjusted R-Squared		0.054	
Observations		19746	
# Obs - # Parameters		17707	

* Robust standard errors, adjusted for clustering by county-quarter, are in parentheses.

TABLE 6
ROBUSTNESS & ALTERNATIVES:
TIME TREND, CLUSTERING, AND SAMPLE SELECTION

	(6-1) (4B-3) with Technology-Specific Time Trend* (MCD FE)			**(6-2)** (4B-3) with County Clustering (MCD FE)			**(6-3)** (4B-3) with "Narrow" Diagnostic Criterion** (MCD FE)			**(6-4)** (4B-3) excluding Large and Low Health Counties*** (MCD FE)		
DEPENDENT VARIABLE						**LL HINDEX**						
EMERGENCY SYSTEMS VARIABLES												
BASIC		-0.021 (0.045)			-0.019 (0.041)			-0.029 (0.048)			-0.008 (0.036)	
E911		**-0.113** **(0.046)**			**-0.118** **(0.044)**			**-0.100** **(0.046)**			**-0.105** **(0.039)**	
EMD		0.018 (0.030)			0.019 (0.040)			0.012 (0.033)			-0.000 (0.030)	
Parametric Restrictions	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value	#Restrict	F-stat	p-value
BASIC = E911	**1**	**5.84**	**0.016**	**1**	**6.14**	**0.013**	1	2.91	0.088	**1**	**7.65**	**0.006**
CONTROL VARIABLES												
QUARTERLY DUMMIES	**21**	**1.77**	**0.016**	7	1.90	0.066	7	1.99	0.053	**7**	**2.61**	**0.011**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**8.31**	**0.000**	**8**	**9.44**	**0.000**	**8**	**7.07**	**0.000**	**8**	**5.01**	**0.000**
PATIENT CHARACTERISTICS	**14**	**7.46**	**0.000**	**14**	**5.43**	**0.000**	**14**	**4.70**	**0.000**	**14**	**6.78**	**0.000**
INCIDENT LOCATION CHARACTERISTICS	8	0.76	0.640	8	1.16	0.320	16	1.07	0.383	16	0.96	0.465
R-Squared		0.152			0.151			0.174			0.149	
Adjusted R-Squared		0.054			0.054			0.056			0.040	
Observations		19746			19746			15791			14038	
# Obs - # Parameters		17695			17709			13822			12447	

* The 8 Quarterly Dummies are interacted with location-specific *initial* technology level, yielding 3 distinct time trends.
Except where noted, robust standard errors, adjusted for clustering by county-quarter, are reported in parentheses.

** Sample is restricted to patients assigned 3-digit ICD-9 Codes between 400-429 at the hospital.

*** Specification excludes counties with (a) population greater than 400,000 or (b) a mortality rate greater than .05.

TABLE 7
THE IMPACT OF EMS VARIABLES ON MORTALITY HAZARD & HOSPITAL COSTS

	(7-1) Cox Proportional Hazard Model stratified by Hospital/MCD combinations*			**(7-2)** Cox Proportional Hazard Model stratified by Hospital/MCD combinations*			**(7-3)** Hospital Costs with Hospital/MCD Fixed Effects**		
DEPENDENT VARIABLE	48 HOUR MORTALITY			6 HOUR MORTALITY			L HOSPITAL COSTS		
EMERGENCY SYSTEMS VARIABLES									
BASIC								**-0.173** **(0.049)**	
E911		*0.649* *(0.150)*			**0.319** **(0.153)**			**-0.189** **(0.048)**	
EMD		1.081 (0.187)			0.685 (0.224)			0.007 (0.033)	
Parametric Restrictions	#Restrict	χ^2	p-value	#Restrict	χ^2	p-value	#Restrict	F-stat	p-value
BASIC = E911							1	0.15	0.699
CONTROL VARIABLES									
QUARTERLY DUMMIES	*7*	8.35	0.303	*7*	**16.19**	**0.023**	**7**	**34.03**	**0.000**
INCIDENT TIME-OF-DAY DUMMIES	**8**	**23.37**	**0.003**	**8**	**28.83**	**0.000**	**8**	**3.55**	**0.000**
PATIENT CHARACTERISTICS	**9**	**49.91**	**0.000**	9	13.66	0.135	**9**	**5.42**	**0.000**
TIME-VARYING INCIDENT LOCATION CHARS.	8	10.14	0.255	8	4.98	0.759	**8**	**3.08**	**0.002**
R-Squared								0.417	
Adjusted R-Squared								0.271	
Log-likelihood		-1727. 574			-389.646				
Observations		19746			19746			19746	
# Obs - # Parameters								15799	

* The hazard coefficient is reported; coefficients represent the proportional effect on the baseline hazard, so that a coefficient of 1.0 corresponds to no effect. The model is stratified, so that each hospital/mcd combination is allowed a separate baseline hazard.

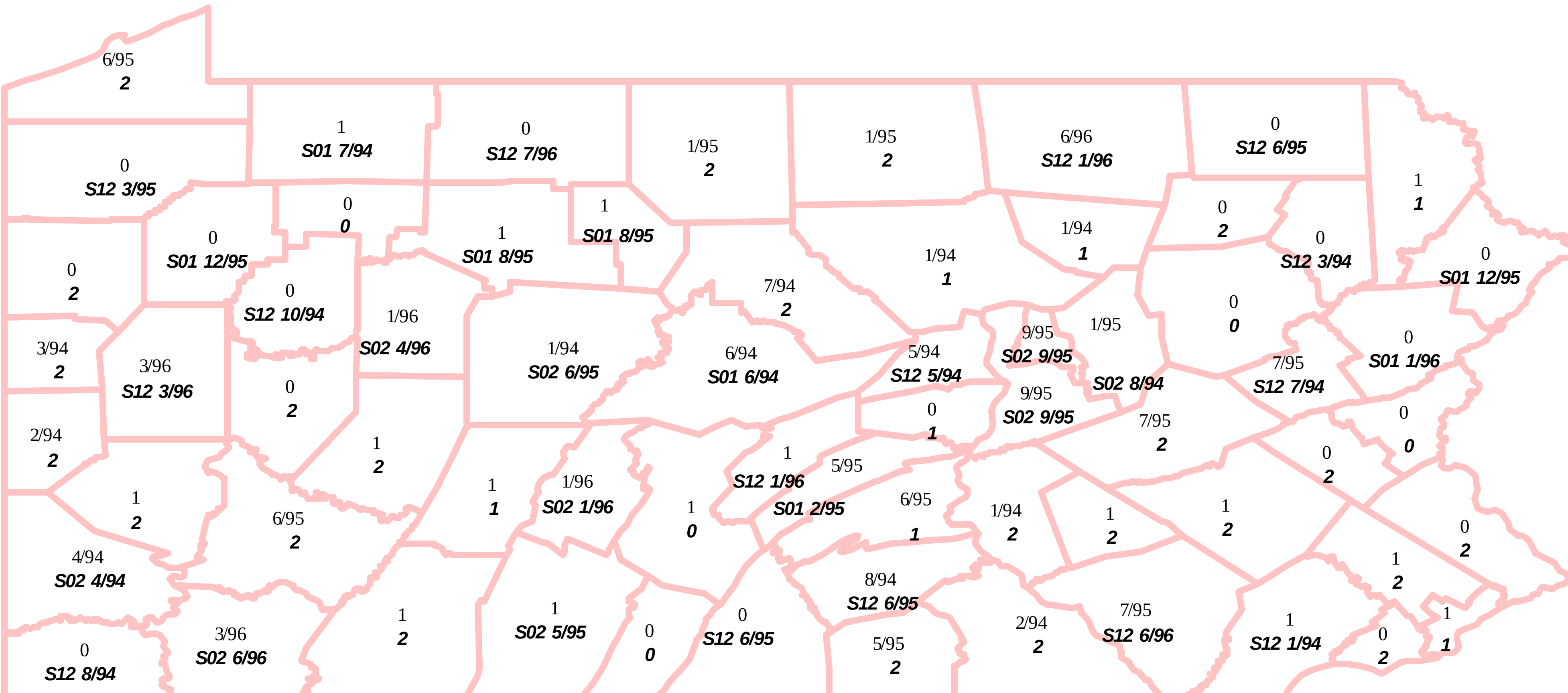
** Specification includes a fixed effect for each hospital/mcd combination.

APPENDIX A
HEALTH INDEX PROBIT EQUATION

Dependent Variable = 48 HOUR MORTALITY	
	HINDEX*
GLASGOW SCORE	
CAT1 (4<=Glasgow<=5)	-0.359 (0.293)
CAT2 (6<=Glasgow<=8)	-0.180 (0.191)
CAT3 (9<=Glasgow<=12)	**-0.351** **(0.170)**
CAT4 (13<=Glasgow<=15)	**-0.835** **(0.137)**
RESPIRATION	
CAT1 (1<=Resp<=5)	*0.505* *(0.260)*
CAT2 (6<=Resp<=9)	-0.337 (0.267)
CAT3 (30<=Resp)	**0.568** **(0.176)**
CAT4 (10<=Resp<=29)	0.294 (0.170)
BLOOD PRESSURE	
CAT1 (1<=Systol<=49)	-0.052 (0.442)
CAT2 (50<=Systol<=75)	-0.012 (0.145)
CAT3 (76<=Systol<=89)	-0.040 (0.136)
CAT4 (>=90)	**-0.801** **(0.115)**
LOW RISK PULSE	
HIGH RISK PULSE (Pulse<=40)	**-0.265** **(0.110)**
Pseudo R-Squared	0.190
# OBS	19746
Log Likelihood	-2412.971

* Specification is based on the critical cut-off points identified in the clinical emergency medicine literature. Coefficients are probit coefficients.

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

IV. Management

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?

V. Adoption Costs

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: