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Author(s): Susan Athey and Scott Stern

Reviewed work(s):

Source: *The RAND Journal of Economics*, Vol. 33, No. 3 (Autumn, 2002), pp. 399-432

Published by: [Blackwell Publishing](#) on behalf of [The RAND Corporation](#)

Stable URL: <http://www.jstor.org/stable/3087465>

Accessed: 02/05/2012 18:19

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The impact of information technology on emergency health care outcomes

Susan Athey*

and

Scott Stern**

We analyze 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 speeds up emergency response. Further analysis using hospital discharge data shows that E911 reduces mortality and hospital costs.

1. 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 critical for identifying the sources of economic growth and evaluating a host of public policies (Summers, 2000).

The benefits 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). Although such quality improvements may

* Stanford University and NBER; athey@stanford.edu.

** Northwestern University, NBER, and the Brookings Institution; s-stern2@northwestern.edu.

The data in this article were supplied by the Emergency Medical Services Office, Pennsylvania Department of Health. The Emergency Medical Services Office specifically disclaims responsibility for analyses, interpretation, or conclusions. We would like to thank Dr. Kum Ham of the Pennsylvania Department of Health, who generously provided his time and answered our questions about the data. We further acknowledge the assistance of 911 coordinators throughout Pennsylvania who completed the survey. Mara Berman provided exceptional research assistance. We are indebted to Iain Cockburn, Edward Glaeser, Guido Imbens, David Meltzer, Paul Riskind, participants at the NBER conference on the Industrial Organization of Health Care (2000), participants at numerous seminars and conferences, the Editor, and an anonymous referee for helpful discussions. We gratefully acknowledge financial support from the National Science Foundation (Athey, grant nos. SBR-9631760 and SES-9983820), a Sloan Foundation Research Fellowship (Athey), and the National Bureau of Economic Research (Stern). Stern completed this article while a Health and Aging Fellow at the National Bureau of Economic Research, whose hospitality is acknowledged. All opinions expressed in this article are the sole responsibility of the authors, and any remaining errors are our own.

be reflected indirectly in economic quantities such as rising wages or increased willingness-to-pay (factors that may be confounded with price inflation in the context of productivity measurement), few studies provide direct evidence about IT's role in increasing service-sector productivity.

Second, IT is a "general-purpose" technology, so its benefits 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 are 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 by 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-biased technical change" is a popular explanation for observed changes in the wage structure (Krueger, 1993; Berman, Bound, and Griliches, 1994; Autor, Katz, and Krueger, 1998). Ignoring organizational design potentially omits a policy-relevant contributor to productivity and may lead to biases in estimating the impact of IT (Bartel, 1996; Athey and Stern, 1998).

This article 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 extent to which the adopting counties have unusual benefits to adoption.

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 seven-digit telephone number that may differ for each emergency service 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 follow a protocol to gather medical information, prioritize ambulance dispatch, and provide 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 using 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 status as recorded by ambulance attendants upon arrival at the scene of the emergency, and (short-term) patient outcomes. We combine this incident-specific information with an original dataset that records 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

¹ See, for example, Brynjolfsson and Hitt (1997), Black and Lynch (2001), Abowd and Kramarz (1999), and Bartel and Sicherman (1999), who confront several challenges in aggregating heterogeneous types of IT in their studies of the impact of IT on wages and measured productivity growth.

² For careful discussions of the empirical evidence, see Ichniowski, Shaw, and Prennushi (1997), Bresnahan and Greenstein (1996), Levy et al. (2000), and Bresnahan, Brynjolfsson, and Hitt (2002).

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

highlight the impact of IT on the timeliness of service provision, we focus on cardiac emergency calls, a group for which 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 health status (as measured by, e.g., blood pressure, respiration, and pulse rates) upon ambulance arrival. We evaluate the gains realized by counties that adopt within our sample period 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 time when 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 affects 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 inclusion of interactions between E911 and demographic variables.

A large clinical literature (discussed below) documents the benefits of rapid medical intervention for health outcomes. We confirm these findings in our data by analyzing the effects of E911 adoption on outcomes measured at the time of hospital discharge. We find that the short-term mortality rate and hospital costs are reduced significantly after E911 adoption. 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 article proceeds as follows. In Section 2 we describe the institutional details of the prehospital emergency response system. Section 3 develops a simple model of emergency health care production and an econometric model to guide the estimation. Sections 4 and 5 describe the data, the adoption process, and how county demographics relate to E911 adoption. Section 6 presents the results. A final section concludes.

2. Information technology and job design in emergency response systems

■ **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 1960s, emergencies were reported to a telephone operator (whose training and equipment were not specialized for 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, 1975). Following a model first developed in Europe, 911 systems were introduced into the United States in 1968. While the scope and details vary, systems typically operate as follows:

- (i) An individual experiencing an emergency calls a local "emergency" number, either 911 or a designated seven-digit number.

⁴ In focusing on cardiac emergencies, we follow several studies about productivity in health care (McClellan and Newhouse, 1997; Cutler, McClellan, and Newhouse, 1999; Cutler et al., 2001; Triplett, 1999). Only a few medical studies analyze the impact of 911 on medical outcomes. Joslyn, Pomrehn, and Brown (1993) show that Basic 911 adoption significantly decreased mortality from out-of-hospital cardiac arrest, but they did not study E911.

- (ii) 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).
- (iii) The call-taker communicates with service agencies for dispatch of emergency personnel.
- (iv) 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 (i) timely response by organizations to customers; (ii) precise information or services tailored to the customer's needs; and (iii) 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 American Heart Association strongly advocates early access to emergency medical services. Clinical studies suggest that the timeliness of administering medical procedures such as cardiopulmonary resuscitation (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., 2001). Precise information about each emergency allows resources to be conserved for time-sensitive emergencies.⁷

□ **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 forgo the use of 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 to contact with an emergency agency. Adoption of Basic 911 often accompanies centralization at the county rather than municipal level, allowing for specialization. A potential cost to centralization is call-takers' unfamiliarity 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 telecommunications 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 readdressing to eliminate duplicates and creating new street addresses for rural areas. This database includes precise information about the location of a telephone in a building or public place, and it can potentially track individual health issues or disabilities.

⁵ Several externalities are associated with emergency response. Public provision lowers the cost to bystanders of providing the public good of reporting emergencies, and public control over emergency response facilities is critical during extreme public emergencies. Privatization experiments have met with little success.

⁶ For example, Larsen et al. (1993) find that, from a level of .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 Advanced Life Support ambulance is delayed. See also Lewis et al., 1982; Cummins et al., 1991; Bonnin, Pepe, and Clark, 1993; and Tresch et al. 1989.

⁷ An 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).

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.

E911 technology is associated with a number of benefits. First, even when a caller knows her location and provides precise directions, this information takes time to communicate. Callers may experience panic or fear, or they may be otherwise unable to provide precise information (e.g., children, nonnative 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 prearrival instructions. Detailed geographic knowledge of an area is no longer essential for call-takers, 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 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" to guide them through the process of eliciting information and providing emergency medical instructions. Call-takers also give instructions for preparing the emergency site for ambulance arrival. These interventions reduce the time it takes to perform key medical procedures, and they reduce the probability that inappropriate procedures are performed before the ambulance arrives. 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 to 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.

3. The empirical framework

■ **The production function for health status.** This article relies on two types of health status measures of 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 $\tau = 0$, a patient experiences cardiac distress. The initial severity of this incident is determined by ξ . The ambulance arrives at time $\tau = \tau^A$. Figure 1 depicts health status, $h(\tau; \xi, \tau^A)$, where higher values indicate more severe symptoms. There are 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.

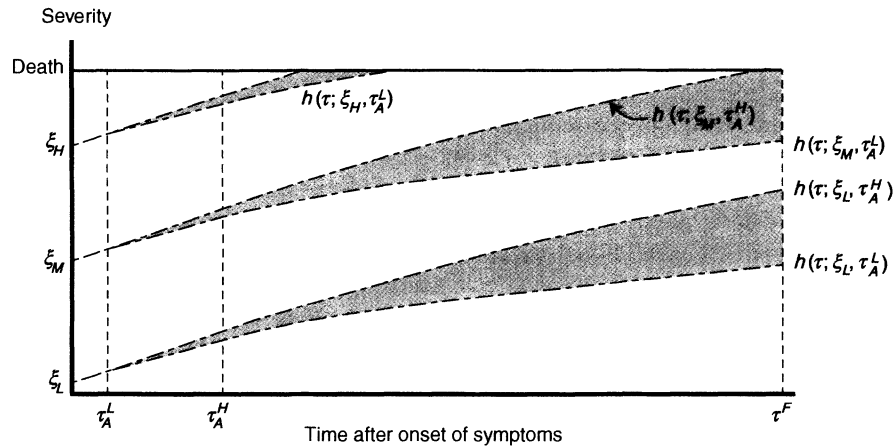
¹⁰ For example, in some E911 counties in Pennsylvania, subscribers can access an emergency response with wireless technology (e.g., an emergency button). These services exploit the technological features of the E911 system to access location information directly.

¹¹ Unfortunately, we cannot estimate the distinct impact of GPS (global positioning system). Only four counties adopted GPS by the end of 1996 (though over half of all counties had adopted some GPS technology by June 2000).

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, back cover).

¹³ Athey and Stern (1999) analyze 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.

FIGURE 1
THE HEALTH STATUS PRODUCTION FUNCTION



A more sophisticated 911 system improves health by improving the distribution of τ^A . To capture this idea, 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 1 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 affect 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). Although improved health for moderately sick patients tends to lower expenditures, the improved survival rate for sick patients may increase both the number of patients and the average cost of those patients.

□ **The estimation strategy.** Our estimation approach is based on “differences-in-differences”: we evaluate how 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 dates. This section formalizes and interprets the assumptions required to make this empirical strategy valid.

We observe the health status of individual patients within a given county, as well as the location of the incident at the MCD (minor civil district) level, which may have its own idiosyncratic characteristics. We use the notation in Table 1.

Following the discussion of the last section, a patient’s measured health status can be written as

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

¹⁴ Thus, we scale our index in terms of 48-hour mortality.
¹⁵ In practice, we use 6-hour and 48-hour mortality; the health care literature suggests that mortality rates decline sharply over the first few hours following the incident (Herlitz et al., 1995).

TABLE 1 Notation

Notation	Interpretation
(t, i, j, k)	Date t , county $i \in \{1, \dots, I\}$, MCD $j \in \{1, \dots, J\}$, patient $k \in \{1, \dots, K\}$.
\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 (e.g., geography and infrastructure).
ξ_k	Unobserved incident severity.

We first decompose county quality into a fixed component and a time-varying component, and we assume that the latter is additive and constant across counties:

Assumption 1. $\chi_i^t = c_i + q^t$.

In Section 6, we relax Assumption 1 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 shorter response times (due to features such as geography and infrastructure), and response times 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). 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:

Assumption 2. f is additively separable in χ_i^t and ψ_j .

Without Assumption 2, our approach identifies the average returns among counties changing their 911 systems during the sample period. But if Assumption 2 fails, the selection of counties that adopt may have returns different from the average level of returns. To address this concern, Section 5 presents evidence on the representativeness of counties adopting 911 systems during our sample; further, in Section 6 we perform a specification test evaluating Assumption 2 directly. Finally, even if adoption is systematically related to returns, our sample period is in the middle of the adoption process, so it is plausible that the estimates identify the impact of IT for locations similar to a typical Pennsylvania county.

We also impose restrictions on unobserved incident 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 incident severity are uncorrelated with the 911 system:

Assumption 3. 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 in less severe incidents). 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

Assumption 4. For some counties i , s_i^t is unchanged over the sample period.

The switching dates for the counties in our sample vary continuously, so Assumption 4 is not strictly necessary. Conceptually, Assumption 4 highlights the idea that the nonswitching counties serve as a “control group” for the trend over time that counties would experience in the absence of technology or EMD adoption.

Under Assumptions 1–4, referred to as “the assumptions of the fixed-effects model,” the average effect of changes in the 911 regime on health outcomes is identified. Imposing a linear functional form for f , our baseline empirical specification is therefore

$$HEALTH_{i,j,k}^t = c_i + q^t + BASIC_i^t(\alpha_{BASIC} - \alpha_{NO911}) + E911_i^t(\alpha_{E911} - \alpha_{NO911}) + EMD_i^t\alpha_{EMD} + \mathbf{x}_k\beta + \mathbf{z}_j'\gamma + \psi_j + \xi_k. \quad (2)$$

We use this model to test hypotheses about the impact of 911 systems ($\alpha_{E911} - \alpha_{NO911}$, $\alpha_{BASIC} - \alpha_{NO911}$, and α_{EMD}) and evaluate several of our maintained assumptions. For example, by allowing α to vary with the time from the adoption date, we can explore 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 also test for interactions between 911 technology and EMD. Finally, the model is overidentified, 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 Assumption 2, these quantities are the same, a testable restriction.

4. The data

■ To implement the econometric approach described in Section 3, we analyze a setting characterized by the availability of unusually rich data, as well as an institutional environment where the assumptions of the fixed-effects 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.

□ **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 emergencies in Pennsylvania for which (i) an ambulance responded to the emergency; (ii) the dispatch resulted in a hospital admission; and (iii) 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 the following:

- (i) Incident location (the MCD) and time of day.
- (ii) The timing and nature of emergency response (e.g., the time between dispatch and arrival at the site of the incident, whether the response was in “lights-and-siren” mode, the type of ambulance and ambulance personnel).
- (iii) Health indicators upon ambulance arrival at the incident scene (e.g., blood pressure, pulse, respiration, and suspected illness)
- (iv) Postincident arrival emergency procedures and transport (e.g., whether transport to hospital is in “lights-and-siren” mode);
- (v) A (confidential) code for the hospital to which the patient is transported.
- (vi) Diagnostic information at the time of hospital admission.
- (vii) 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 2000.¹⁶ 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, or E911) and the presence or absence of EMD for every county in Pennsylvania at each point in our sample period (Table 2 provides precise definitions for each type of adoption). Finally, we incorporate demographic and weather data at the zip code, MCD, hospital, and county levels. Table 2 lists variables and sources.

□ **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 whose “suspected illness” reported on the ambulance report was cardiac, and only patients who are diagnosed with a cardiac condition upon admission to a hospital (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:

- (i) Emergencies that do not require “lights-and-sirens” on both the outgoing dispatch call and during the ambulance transport to the hospital.
- (ii) Patients less than 20 years old and pregnant patients.
- (iii) Transports from one medical facility to another.
- (iv) Incidents in the two largest metropolitan areas of Pennsylvania: Philadelphia and Pittsburgh.¹⁹
- (v) 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.
- (vi) Incidents where less than \$50 of hospital charges are incurred.

After eliminating observations for which either the incident county or one of the key health status measures is missing, our final dataset consists of 19,746 observations. About 55% of patient incidents occurred 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.

□ **Variables and summary statistics.** For the variables used in our analysis, Table 2 provides variable names and definitions, while Table 3 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

¹⁶ For each Emergency Response Center, we gathered data about the timing of 911 and EMD adoption, the structure and management of the Emergency Response Center, the county’s ambulance services, and the costs of adoption. The follow-up survey confirmed the timing of adoption and filled in incomplete responses. The complete MIT Public Safety Answering Point (PSAP) Survey is available at www.stanford.edu/~athey/911survey.pdf. Overall, the survey is more comprehensive than the data employed in our earlier cross-sectional analysis (Athey and Stern, 2000a).

¹⁷ The initiation of either a higher level of 911 technology or EMD is a 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 because a patient’s in-hospital diagnosis reflects his health on arrival, itself a function of emergency response timeliness. Our results are, however, robust to narrower sample definitions.

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.

TABLE 2 Variables^a and Definitions

Variable	Full Variable Name	Definition	Source
Raw Measures of Patient Health Status and Patient Expenditure			
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	PA EMS; Medicare cost reports
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	
Constructed Patient Health Status Measures			
HIGH RISK BP	High-risk blood pressure dummy	HIGH RISK BP = 1 if BLOOD PRESSURE < 90	PA EMS; 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 HOUR MORTALITY from probit on blood pressure, respiration, pulse, and Glasgow categories (see Appendix A)	
County-Level Emergency Response System Measures			
NO 911	No 911 dummy	“No 911” in county on INCIDENT DATE	MIT PSAP survey
BASIC	Basic 911 dummy	“Basic 911” in county on INCIDENT DATE, defined as countywide 911 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			
INCIDENT DATE	Date of emergency incident	Date of emergency incident (between 1/1/1994 and 12/31/1996)	PA EMS
QUARTER DUMMIES	Quarterly dummies	Eight quarterly dummies based on INCIDENT DATE	
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	
OTHER INSURANCE	Other insurance category dummy	OTHER INSURANCE = 1 if MEDICARE, MEDICAID, PRIVATE, and SELF_PAY = 0	

TABLE 2 *Continued*

Variable		Full Variable Name	Definition	Source
Patient Location Demographics				
Patient Billing Address Zip Code Demographics (ZIP_*)				
ZIP	PERCAP INCOME	Per-capita income	Per-capita income (1990 Census)	U.S. Census Bureau Zip Code Gazetteer
ZIP	% BLACK	Percentage African-American	Percentage African-American in zip code population (1990 Census)	
ZIP	% FOREIGN	Percentage foreign-born	Percentage foreign-born in population (1990 Census)	
ZIP	% HIGH SCHOOL+	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 number of ambulances appearing in PA EMS data in MCD in quarter of INCIDENT	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)	U.S. 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)	AHA Survey PA EMS
C	HOSPITALS	Total hospitals in county	Total distinct hospitals in county	
C	CALL VOLUME	Total emergency patients in county in given month	Total emergency patients appearing in PA EMS data in county in INCIDENT month	

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

of intermediate health status, and to 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

²⁰ Although these are 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 Glasgow coma score is a specialized emergency medicine index, ranging from 3 to 15 (higher scores indicate lower severity), reflecting patient alertness and responsiveness (www.trauma.org).

TABLE 3 Summary Statistics

Variable		Mean	Standard Deviation
Raw Measures of Patient Health Status and Expenditure			
BLOOD PRESSURE		137.147	49.467
RESPIRATION		21.404	8.113
PULSE		85.815	34.608
GLASGOW		14.112	2.943
48 HR MORTALITY		.035	.183
6 HR MORTALITY		.008	.090
TOTAL COSTS		6,400.319	7,907.794
Constructed Patient Health Status Measures			
HIGH RISK BP		.103	.304
HIGH RISK PULSE		.065	.247
County-Level Emergency Response System Measures			
NO 911		.148	.355
BASIC		.172	.377
E911		.679	.467
EMD		.490	.500
Patient Characteristics			
MALE		.512	.500
AGE		70.221	12.970
MEDICARE		.676	.468
MEDICAID		.047	.212
PRIVATE		.205	.404
SELF_PAY		.009	.092
OTHER INSURANCE		.064	.244
Patient and Incident Location Demographics			
<i>Patient Billing Address Zip Code Demographics (ZIP_*)</i>			
ZIP	PERCAP INCOME	13,656.460	4,629.954
ZIP	% BLACK	.042	.105
ZIP	% FOREIGN	.024	.022
ZIP	% HIGH SCHOOL+	.177	.042
<i>MCD-Level Incident Location Pre-Hospital Infrastructure (M_*)</i>			
M	QUARTERLY AMBULANCES	5.158	4.147
M	ALS SHARE	.758	.302
M	PRECIPITATION	.251	.434
M	SNOWFALL	.056	.230
M	SNOW DEPTH	.070	.256
M	MAX TEMP	.020	.139
M	MIN TEMP	.027	.164
<i>County-Level Incident Location Demographics (C_*)</i>			
C	POPULATION	273,136.900	192,711.300
C	DENSITY	579.971	687.654
C	PERCAP INCOME	18,244.870	4,042.793
C	TOTAL HOSPITALS	4.209	2.162
C	CALL VOLUME	307.268	51.537

Unfortunately, hospital outcome data are available *only* for the first hospital to which the patient is admitted. If (i) the patient is transferred from the initial hospital to a hospital with more advanced cardiac facilities or (ii) the patient is discharged and readmitted in 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 prehospital care should be most pronounced during the initial hours following an incident, and such medium-term measures are likely to 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 that (i) accounts for nonlinearities and nonmonotonicities in the relationship between the raw measures and patient health; (ii) aggregates the individual measures into a single index that distinguishes among patients more finely; and (iii) is scaled according to the predicted probability of short-term mortality.

A substantial literature on clinical emergency medicine develops 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 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 one if systolic blood pressure is less than 90) and HIGH RISK PULSE (equal to one 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 (i) the critical cutoff points for BLOOD PRESSURE, RESPIRATION, and GLASGOW suggested by one leading scoring system (called the Revised Trauma Score (RTS) system)²⁴ and (ii) HIGH RISK PULSE.²⁵ We then perform a probit regression of 48 HOUR MORTALITY on the full set of these categorical variables (reported in Table A1 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, given her condition when the ambulance arrives and assuming that she receives an average level of care after the ambulance arrives.

²¹ Only .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.

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 assigned a number; the score is a weighted average of these score components (Svirbely and Sriram, 2001).

²³ Scores for specific diagnoses such as cardiac emergency tend to be designed for use after the patient's arrival at the hospital; although our dataset is composed of all cardiac emergencies, many existing scores are tailored to narrower diagnoses such as cardiac arrest.

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, so we choose to include it in our analysis.

²⁶ The mortality regression results are consistent with the clinical literature. While multicollinearity makes interpreting individual coefficients difficult, there is a monotone relationship between survival and severity categories in more parsimonious specifications (Athey and Stern, 2000b). All our results are robust to the use of alternative health score specifications.

5. Characteristics of counties that adopt before, during, and after the sample period

■ 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. The estimates 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 probably realize returns that are close to the average level of population returns.

□ **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 PSETP reduced the monetary costs of adoption in two ways. First, it authorized each county to implement a telephone tax on its residents to pay for 911 services (between \$0.75 and \$1.50 a resident depending on the size of the county). Second, 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 either upgraded their level of technology, adopted EMD, or both. Many of the counties that did 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. Readdressing requires coordination with local post offices and public utilities, and typically it must be approved by each municipality in a county. Before 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 startup cost data are unavailable, we estimate from several examples that the startup 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, consistent with the hypothesis that the costs of adoption play an important role in the adoption process (Athey and Stern, 1999, 2000a).²⁹

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

²⁷ The legislation states that the toll-free number 911 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.state.pa.us).

²⁸ Berks County, Pennsylvania (population 336,000) reports E911 startup costs of approximately \$3 million and annual operating costs of over \$2.3 million, of which only part can be attributed to incremental costs associated with E911. Employing nine call-takers and an administrative staff, the Berks County E911 Center is slightly larger than the average center in our sample.

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 affect the probability of adoption (Athey and Stern, 1999, 2000a).

delays due to long negotiations with municipalities and police departments over the control and employment of call-takers.³⁰

PSETP also affected adoption of EMD. 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 also investigated potential changes in the 911 system or the health care infrastructure that might confound the analysis of technology adoption and EMD. We found that the following factors relating to ambulance infrastructure 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 911 (five of the eight counties that switched from No 911 to Basic reported that the switch coincided with additional centralization), only four out of twenty-three E911 adopters report a change in centralization 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.

□ **Comparing characteristics of counties by adoption patterns.** Consider the specific changes in 911 systems that occur during our sample period, 1994–1996. Twenty-two 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 that begin the sample with BASIC, 14 of them 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 nonswitchers can be usefully divided into two groups: those who adopt 911 technology prior to 1994 (presample adopters) and those who adopt the technology after 1996 (postsample adopters). Each of the three groups—within sample adopters, presample adopters, and postsample adopters—contains one-third of the counties. We further subdivide the presample adopters into the very early adopters (before 1992) and the early adopters (1992–1993). Recall that three distinct types of technology switching occur in our sample: No 911 to Basic, No 911 to E911, and Basic to E911.

Table 4 presents county-level average characteristics for each of seven different “regimes,” according to their presample technology and their adoption behavior between 1994 and 1996.³³ While these groups are fairly similar, several differences are useful to note. First, counties that maintain Basic or switch from No 911 to Basic during the sample period have smaller total populations and lower densities than the sample average. While within-sample Basic adopters have average per-capita income, counties maintaining a low level of technology have a per-capita income slightly lower than average. In contrast, counties that adopted E911 prior to 1994 are larger and more densely populated, and they have slightly older patients (each effect is pronounced for

³⁰ Delays often involved negotiations over peripheral issues. In one county, E911 adoption was delayed by 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.

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

³³ The means in Table 4 weight each county equally; in contrast, Table 3 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.

TABLE 4 County Characteristics by Type of Switching Behavior

	Regime						
	Nonswitchers				Switchers		
	No 911	Basic	Pre-1992 E911 Adopter	1992–1993 E911 Adopter	No 911 to Basic	No 911 to E911	Basic to E911
Average County Characteristics by Regime							
Number of counties	5	6	4	19	8	9	14
C POPULATION	128,983.20 (150,763.50)	68,393.83 (59,513.80)	187,883.80 (183,492.20)	233,823.80 (195,661.00)	53,841.13 (41,709.36)	92,705.33 (59,126.33)	113,849.60 (111,117.20)
C PERCAP INCOME	14,881.40 (2,501.56)	15,563.83 (1,247.87)	16,511.75 (3,560.91)	17,824.95 (4,159.73)	16,474.50 (1,496.24)	14,966.11 (1,529.32)	15,521.57 (1,972.43)
C 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)
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	.029 (.013)	.025 (.021)	.048 (.023)	.045 (.021)	.021 (.017)	.030 (.008)	.024 (.017)

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 the middle of the overall distribution of adopters. Finally, while a more systematic analysis of mortality will be conducted in the next section, note that the earliest adopters of E911 have the highest mortality rates, and that counties that switched from Basic to E911 have a somewhat lower mortality rate.

6. 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 to our analysis, including postadoption 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 prehospital emergency response productivity.

Except where noted, the analysis focuses on the probability of mortality or a poor intermediate health 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

³⁴ 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 because we believe the health productivity trend may be different in these highly urbanized areas.

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

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.

□ **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 5 focuses on HIGH RISK BLOOD PRESSURE. In column 1, we report a simple cross-sectional OLS regression that relates the 911 technology and time trend using quarterly dummy variables. Not only is there no statistical relationship between 911 technology and outcomes, but the coefficients are extremely small (and, for E911 and EMD, the point estimates are positive). In contrast, column 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. These findings are strengthened in column 3 when we incorporate fixed effects for each of 1997 MCDs, 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 geographic variation in the intermediate health status of patients is critical. Variation in health across locations most likely arises because of differences in demographics and infrastructure. For example, localities differ in the distance of patients to hospitals and ambulances, as well as traffic. Geographic controls for observable factors (such as population, density, and per-capita income) explain little of this heterogeneity in health. We therefore incorporate fixed geographic effects in our empirical models, so that our estimates reflect the average realized benefit to adoption for counties that adopt during our sample period.

The specifications reported in Table 6 explore these findings in more depth, by including a rich set of control variables and considering alternative dependent variables. We add controls for patient characteristics (including demographics associated with the patient’s home zip code), and we control for changes in the ambulance infrastructure and the monthly call volume experienced in each county. 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 column 1 of Table 6 to column 3 of Table 5 demonstrates that the inclusion of additional controls does not affect our main findings.³⁸ Column 2 of Table 6 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

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 does *not* have a significant relationship with BASIC or E911 adoption, suggesting that the size of the patient pool for cardiac emergencies is not significantly affected by adoption.

³⁸ Our results about the control variables indicate that health status is lower for patients who are male, older, or whose home zip code contains a high percentage of African-American residents. Other factors, notably weather and call volume, tend to be statistically and quantitatively insignificant. Inclusion or exclusion of these controls does not affect the E911 results.

TABLE 5 Impact of EMS Variables on High-Risk Blood Pressure^a

				(2)			(3)		
(1)				EMS Variables,			EMS Variables,		
EMS Variables and				Quarterly Dummies, and			Quarterly Dummies, and		
Quarterly Dummies				County Fixed Effects			MCD Fixed Effects		
Dependent Variable				HIGH RISK BP					
Emergency Response System (EMS) Variables									
BASIC		-.004			-.008			-.002	
		(.010)			(.012)			(.012)	
E911		.006			-.041			-.045	
		(.009)			(.012)			(.013)	
EMD		.005			.009			.011	
		(.006)			(.008)			(.010)	
<i>Parametric Restrictions</i>	# Restrict	<i>F</i> -stat	<i>p</i> -value	# Restrict	<i>F</i> -stat	<i>p</i> -value	# Restrict	<i>F</i> -stat	<i>p</i> -value
BASIC = E911	1	1.90	0.169	1	7.72	0.006	1	11.89	.0006
Quarterly Dummies (Q1 1994 is excluded quarter)									
Q2 1994		.007			.007			.008	
		(.010)			(.006)			(.007)	
Q3 1994		.006			-.001			.006	
		(.011)			(.007)			(.008)	
Q4 1994		.014			.008			.013	
		(.011)			(.007)			(.008)	
Q1 1996		-.002			.002			.004	
		(.010)			(.007)			(.008)	
Q2 1996		.010			.016			.017	
		(.010)			(.008)			(.008)	
Q3 1996		.005			.009			.011	
		(.012)			(.010)			(.011)	
Q4 1996		.018			.027			.028	
		(.011)			(.008)			(.009)	
<i>R</i> ²		.001			.017			.129	
Adjusted <i>R</i> ²		.001			.014			.031	
Number of observations		19,746			19,746			19,746	

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

exclusion of demographic and incident-location controls. In summary, 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 Section 4. We follow the bulk of research on survival probabilities and use the log-odds ratio, $LL\ HINDEX = \ln(HINDEX/(1 - HINDEX))$, ensuring that the probability of survival predicted by the specification falls between zero and one and reducing the skew of HINDEX (Dawson-Saunders and Trapp, 1994). The results in column 3 of Table 6 show 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

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-effects 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 $\ln(\text{HINDEX})$, and we can include or exclude detailed patient characteristics or time-varying incident characteristics with no qualitative impact on the results. In all specifications, we reject the hypothesis that $\text{BASIC} = \text{E911}$ at the 1% level.

As suggested in Section 3, it is possible to perform a specification test by estimating whether the returns to switching from No 911 to Basic ($\lambda_{\text{NO911_BASIC}}$) plus the returns to switching from Basic 911 to E911 ($\lambda_{\text{BASIC_E911}}$) are equal to the returns to switching from No 911 to Basic 911 ($\lambda_{\text{NO911_E911}}$). We test this by estimating column 3 of Table 6 but estimating a separate coefficient for each switching pattern. The estimates (with standard errors in parentheses) are $\hat{\lambda}_{\text{NO911_BASIC}} = -.012 (.046)$, $\hat{\lambda}_{\text{BASIC_E911}} = -.091 (.040)$, and $\hat{\lambda}_{\text{NO911_E911}} = -.112 (.041)$; we cannot reject the hypothesis that $\lambda_{\text{NO911_BASIC}} + \lambda_{\text{BASIC_E911}} = \lambda_{\text{NO911_E911}}$.

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 a precise location and direct an ambulance to that location, and that timeliness has been improved by the adoption of advanced information technology. If the primary benefits came from using the standard number 911 for access, then Basic and E911 should have a similar impact.⁴⁰ Our EMD findings are less conclusive, since the benefits of EMD may be realized 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

□ **Implications and extensions.** *E911 and the distribution of intermediate health outcomes.* Our theoretical framework suggests that the distribution of patient outcomes should be shifted by E911. Whereas Tables 5 and 6 offer evidence that average intermediate health status is improved by E911 adoption, they provide 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 more severely ill patients. 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. We both split the sample according to these characteristics (performing separate regressions for each group) and examine 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 vary according to the specification.

Second, Figure 2 provides a direct assessment of how E911 shifts the distribution of intermediate health status.⁴² The figure is constructed by selecting the subsample of patients living counties adopting E911 during the sample period. The dotted line represents the cdf of HINDEX

³⁹ The probability derivative implied by a coefficient β is equal to $(.035)(1 - .035) \cdot \beta$ (for a dichotomous independent variable, this calculation yields a close approximation of the incremental effect of the variable). By construction, elasticities with respect to the survival probability (i.e., $(1 - \text{HINDEX})$) are much smaller in magnitude.

⁴⁰ Of course, Basic 911 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 call-takers' unfamiliarity with remote geographic areas.

⁴¹ Within our sample, only 75% of ambulances have paramedic attendants (who are required for prehospital defibrillation or administration of drugs), indicating that paramedics may be scarce. However, within our sample, EMD adoption does not increase the likelihood of a paramedic on board.

⁴² 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 $\text{HINDEX} \leq .015$ and approximately 1 for $\text{HINDEX} \geq .35$.

TABLE 6 **Impact of EMS Variables on Alternative Intermediate Health Status Measures**

	(1)				(2)			(3)		
	EMS and Control Variables and MCD Fixed Effects				EMS and Control Variables and MCD Fixed Effects			EMS and Control Variables and MCD Fixed Effects		
Dependent Variable	HIGH RISK BP				HIGH RISK PULSE			LL HINDEX		
Emergency Response System Variables										
BASIC	−.005 (.012)				−.010 (.011)			−.019 (.036)		
E911	−.043 (.012)				−.035 (.012)			−.118 (.038)		
EMD	.009 (.010)				.007 (.009)			.019 (.029)		
Parametric Restrictions	# Restrict	F-stat	p-value	# Restrict	F-stat	p-value	# Restrict	F-stat	p-value	
BASIC = E911	1	10.54	.001	1	6.55	.011	1	8.43	.004	
Control Variables										
Patiet Demographic & Insurance Characteristics										
MALE	.027 (.005)				.017 (.004)			.071 (.014)		
AGE 46–55	−.012 (.014)				.002 (.010)			−.001 (.037)		
AGE 56–65	.027 (.013)				.017 (.010)			.108 (.034)		
AGE 66–75	.028 (.013)				.034 (.010)			.150 (.035)		
AGE 75+	.009 (.013)				.011 (.009)			.108 (.033)		
MEDICAID	.006 (.012)				−.009 (.009)			.004 (.035)		
PRIVATE	.010 (.008)				.008 (.007)			.005 (.023)		
SELF.PAY	.052 (.031)				.064 (.025)			.156 (.083)		
OTHER INSURANCE	.001 (.011)				.005 (.009)			−.005 (.033)		
Patient Billing Address Zip Code Characteristics										
ZIP.%BLACK	.152 (.043)				.119 (.033)			.444 (.121)		
ZIP.%FOREIGN	.105 (.186)				.136 (.159)			.349 (.556)		
ZIP.L PERCAP INCOME	.019 (.020)				.014 (.019)			.056 (.059)		
ZIP.%HIGH SCHOOL+	−.061 (.133)				−.054 (.119)			−.163 (.387)		

TABLE 6 *Continued*

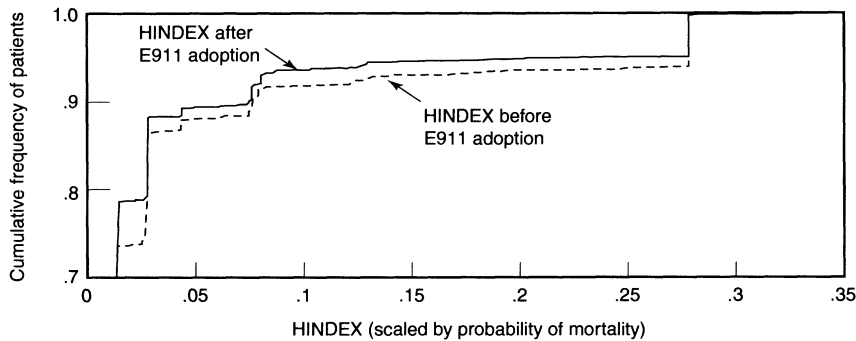
	(1)	(2)	(3)
	EMS and Control Variables and MCD Fixed Effects	EMS and Control Variables and MCD Fixed Effects	EMS and Control Variables and MCD Fixed Effects
Dependent Variable	HIGH RISK BP	HIGH RISK PULSE	LL HINDEX
Time-varying Incident Location Characteristics			
<i>MCD Level</i>			
L M.QUARTERLY AMBULANCES	−.004 (.006)	−.001 (.005)	−.008 (.018)
M.ALS SHARE	−.015 (.017)	−.008 (.014)	−.036 (.051)
M.SNOWFALL	.003 (.011)	−.004 (.008)	−.021 (.029)
M.SNOW DEPTH	.001 (.008)	.008 (.007)	.030 (.024)
M.PRECIPITATION	−.005 (.005)	−.005 (.004)	−.020 (.017)
M.MAX TEMP	.013 (.018)	.002 (.015)	.027 (.047)
M.MIN TEMP	.026 (.017)	.019 (.015)	.057 (.051)
<i>County Level</i>			
L C.CALL VOLUME	.009 (.008)	.001 (.006)	.013 (.022)
Constant	.225 (.204)	.246 (.181)	−3.399 (.605)
<i>Incident Timing</i>			
<i>Parametric Restrictions</i>	# Restrict F-stat p-value	# Restrict F-stat p-value	# Restrict F-stat p-value
QUARTERLY DUMMIES	7 2.91 .005	7 1.80 .082	7 2.11 .040
INCIDENT TIME-OF-DAY DUMMIES	8 13.30 .000	8 13.20 .000	8 8.32 .000
R ²	.141	.152	.151
Adjusted R ²	.042	.055	.054
Number of observations	19,746	19,746	19,746
Observations — Parameters	17,709	17,709	17,709

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

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 2 illustrates that the distribution of HINDEX improves according to first-order stochastic dominance after E911 adoption, reinforcing our regression results from Table 6. 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,

FIGURE 2
CUMULATIVE DISTRIBUTION OF HINDEX BEFORE AND AFTER E911 ADOPTION



in the fraction of patients who fall into the healthiest category, characterized by HINDEX less than or equal to .014, increases from .737 to .785 following E911 adoption.

Figure 2 suggests that the impact of E911 is most dramatic on the most critically ill patients, a hypothesis reinforced by several robustness checks. First, though Figure 2 does not control for patient demographics, location variables, or a time trend, their inclusion does not affect our findings.⁴³ Furthermore, for each dimension of raw health status (examined in isolation), E911 adoption reduces the proportion of patients in the worst category for that dimension.

Evidence for postadoption learning. We are interested in the timing of the impact of E911 for at least two reasons. First, we would like to verify that the impact attributed to E911 does not 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 these issues, we estimate a regression similar to column 3 of Table 6 but include dummy variables for each of nine 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).⁴⁴

Figure 3 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).⁴⁵ The results are suggestive, though wide confidence intervals make us cautious in our interpretation.⁴⁶ The mortality predictions associated with quarters prior to adoption are higher than all but the first mortality predictions for quarters since adoption. Indeed, whereas all but one of the quarters prior to adoption are associated with a mortality rate higher than .029, the mortality rates for all but the first quarter since adoption 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 3 is consistent with 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 5 and 6 coefficients may be conservative, because late-adopting counties may not have realized their full productivity gains by the end of 1996.

⁴³ For example, the difference between the two cdf's 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 column 3 of Table 6 but excluding the E911 technology adoption variable.

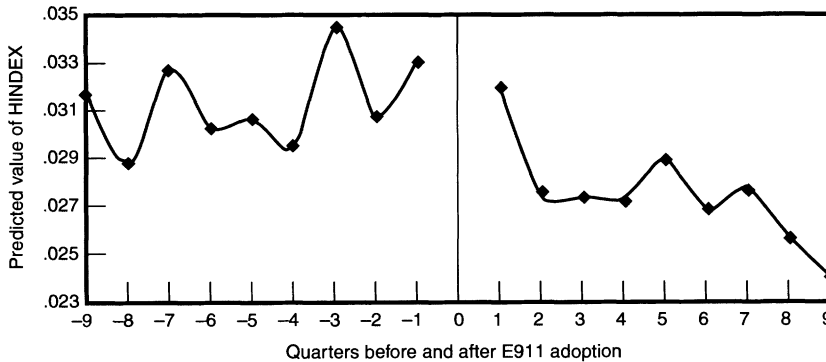
⁴⁴ Because adoption dates differ across counties, each adoption coefficient is estimated using a different group of counties. For example, counties adopting in June 1994 will not contribute to the “3 quarters prior to adoption” coefficient.

⁴⁵ The coefficients are derived from a regression of $LL(\text{HINDEX})$ on dummy variables for the quarters before and after adoption, as well as the control variables used in column 3 of Table 4.

⁴⁶ These results are robust to several alternative specifications and intermediate health status measures.

FIGURE 3

EFFECT OF TIME BEFORE AND AFTER E911 ADOPTION ON HINDEX



Technology and job design interaction effects. Our discussion in Section 2 highlighted the potential importance of interaction effects between IT and job design: does the adoption of more advanced IT increase the returns to changing 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. The parameters corresponding to these incremental returns are identified by the assumptions of the fixed-effects model.⁴⁷

Table 7 reports the results. Letting NO EMD be an indicator equal to one for dates prior to the adoption of EMD, we relax column 3 of Table 6 by replacing the technology and EMD variables with five dummy variables for each of five 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).

We perform a number of tests concerning interaction effects between 911 technology and EMD, including separate tests for complementarity between EMD adoption and (i) NO 911 to BASIC adoption; (ii) NO 911 to E911 adoption; (iii) BASIC to E911 adoption; and (iv) a joint test of restrictions implied by (i)–(iii).⁴⁸ Rather than providing support for 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.

Diffusion of E911 technology. 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 this prediction is true, the measured productivity benefits associated with adopters may be biased, yielding an estimate that is greater than the true benefit to an average *potential* adopter. While Section 5 presents some evidence that our sample period captures

⁴⁷ 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 Assumption 2, comparing parameters across counties is valid.

⁴⁸ We also conducted the specification test suggested in Section 3, allowing each type of switch to have a separate coefficient, testing the restrictions implied by Assumption 2. We cannot reject the hypothesis that these restrictions are valid, so we maintain Assumption 2 for the analysis.

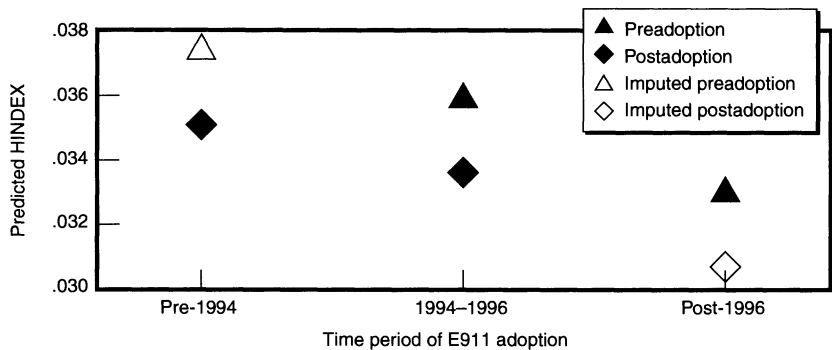
TABLE 7 **Impact of EMS Variables on Intermediate Health Status: Interaction Effects.^a**
Dependent Variable = LL HINDEX

EMS Interactions Including Patient and Incident Location Characteristics (MCD FE)			
Emergency Response System Variables			
BASIC * NO EMD		-.041 (.041)	
E911 * NO EMD		-.144 (.044)	
NO 911 * EMD		-.061 (.071)	
BASIC * EMD		-.018 (.064)	
E911 * EMD		-.116 (.042)	
<i>Parametric Restrictions</i>	# Restrict	<i>F</i> -stat	<i>p</i> -value
PRACTICE TESTS			
NO 911 = BASIC	2	.65	.522
NO 911 = E911	2	5.57	.004
BASIC = E911	2	4.52	.011
EMD = NO EMD	3	.58	.631
INTERACTION TESTS			
EMD * BASIC – EMD * NO 911 – NO EMD * BASIC = 0	1	.97	.325
EMD * E911 – NO EMD * E911 – EMD * NO 911 = 0	1	1.34	.247
(EMD * E911 + NO EMD * BASIC) – NO EMD * E911 – EMD * BASIC = 0	1	.01	.934
JOINT TEST OF PREVIOUS THREE	2	.71	.490
Control Variables			
QUARTERLY DUMMIES	7	2.07	.043
INCIDENT TIME-OF-DAY DUMMIES	8	8.30	.000
PATIENT CHARACTERISTICS	14	7.50	.000
TIME-VARYING INCIDENT LOCATION CHARS.	8	.83	.576
<i>R</i> ²		.151	
Adjusted <i>R</i> ²		.054	
Number of observations		19,746	
Observations – Parameters		17,707	

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

adoption by “average” counties, this subsection 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 adopters after adoption, and post-1996 adopters. We estimate a regression similar to column 3 of Table 6, 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

FIGURE 4
DIFFUSION OF E911 AND SURVIVAL RATES



HINDEX value for each group, using the sample means of all variables except for the technology adoption dummy variables, and plot these in Figure 4.⁴⁹ The difference between preadoption and postadoption 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 from that in Table 6 because the specification does not include MCD fixed effects). We apply this estimate of the impact of E911 to counties not adopting during the sample period, to illustrate the *predicted* levels of HINDEX for presample adopters in the absence of adoption and postsample 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. Within-sample E911 adopters have the *highest* mortality probabilities of all groups prior to E911 adoption but, after adoption, “leapfrog” over presample adopters to a point just above the postsample 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 not associated with poor health status both prior to and after adoption (which would be consistent with selection 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), as well as the greatest incremental improvement in 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 1994.⁵⁰

Alternative time trends, correlated observations, and sample limitations. In this subsection, we evaluate the sensitivity of the differences-in-differences estimation strategy to the assumptions of the fixed-effects model and our sampling scheme. Table 8 reports a subset of these robustness checks; we also discuss ancillary (unreported) results that shed further light on our main findings.

⁴⁹ The points on the figure represent the predicted values of HINDEX, calculated from a regression that is the same as the one reported in column 3 of Table 6, 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.

⁵⁰ 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 of HINDEX in a county in the first quarter of 1994). We have not found consistent evidence for interaction effects that would suggest substantial selectivity in our sample.

TABLE 8 **Robustness and Alternatives: Time Trend, Clustering, and Sample Selection.**
Dependent Variable = LL HINDEX

	(1) Table 6 Column (3) with Technology-Specific Time Trend ^a (MCD FE)			(2) Table 6 Column (3) with Standard Errors Adjusted for Clustering by County (MCD FE)			(3) Table 6 Column (3) with “Narrow” Diagnostic Criterion ^b (MCD FE)			(4) Table 6 Column (3) Excluding Large and Low Health Counties ^c (MCD FE)		
Emergency Response System Variables												
BASIC	−.021 (.045)			−.019 (.041)			−.029 (.048)			−.008 (.036)		
E911	−.113 (.046)			−.118 (.044)			−.100 (.046)			−.105 (.039)		
EMD	.018 (.030)			.019 (.040)			.012 (.033)			−.000 (.030)		
<i>Parametric Restrictions</i>	# Restrict	<i>F</i> -stat	<i>p</i> -value	# Restrict	<i>F</i> -stat	<i>p</i> -value	# Restrict	<i>F</i> -stat	<i>p</i> -value	# Restrict	<i>F</i> -stat	<i>p</i> -value
BASIC = E911	1	5.84	.016	1	6.14	.013	1	2.91	.088	1	7.65	.006
Control Variables												
QUARTERLY DUMMIES	21	1.77	.016	7	1.90	.066	7	1.99	.053	7	2.61	.011
INCIDENT TIME-OF-DAY DUMMIES	8	8.31	.000	8	9.44	.000	8	7.07	.000	8	5.01	.000
PATIENT CHARACTERISTICS	14	7.46	.000	14	5.43	.000	14	4.70	.000	14	6.78	.000
INCIDENT LOCATION CHARACTERISTICS	8	.76	.640	8	1.16	.320	16	1.07	.383	16	.96	.465
<i>R</i> ²		.152			.151			.174			.149	
Adjusted <i>R</i> ²		.054			.054			.056			.040	
Number of observations		19,746			19,746			15,791			14,038	
Observations — Parameters		17,695			17,709			13,822			12,447	

^a The eight quarterly dummies are interacted with location-specific initial technology level, yielding three distinct time trends. Except where noted, robust standard errors, adjusted for clustering by county-quarter, are reported in parentheses.

^b Sample is restricted to patients assigned 3-digit ICD-9 codes between 400 and 429 at the hospital.

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

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 whether adopting counties are unusual in some way (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 there is no significant difference 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 column 1 of Table 8, 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 of observations 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, Duflo, and Mullainathan, 2001), perhaps from persistent shocks to 911 center productivity. Column 2 of Table 8 reports a specification in which 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 relatively stable but for the adoption of 911 technology and EMD.⁵¹

Finally, we consider alternative sampling schemes. First, we consider a narrower cardiac emergency definition, as defined by the ICD-9 codes assigned to patients at the admitting hospital. So far, our sample is defined according to a generous definition of cardiac emergency (3-digit ICD-9 codes from 400 to 459), while column 3 of Table 8 restricts attention to 3-digit ICD codes from 400 to 429, focusing only on more severe cardiac conditions. Though this restriction eliminates 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. The specification reported in column 4 provides a final sampling check, where we exclude highly populated and high-mortality counties. This specification allows us to test in more detail how the results depend on demographic characteristics or the pre-existing health distribution of adopting counties. The results in column 4 are similar to our earlier results.

□ **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 analyses complement our prior results in two ways. First, we investigate whether longer-term 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 and 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 to interpret our 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 by examining how technology and EMD affect 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 ambulance dispatch. 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

⁵¹ 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.

TABLE 9 Impact of EMS Variables on Mortality Hazard and Hospital Costs

	(1) Cox Proportional Hazard Model Stratified by Hospital/MCD Combinations ^a				(2) Cox Proportional Hazard Model Stratified by Hospital/MCD Combinations ^a			(3) Hospital Costs with Hospital/MCD Fixed Effects ^b		
Dependent Variable	48 HOUR MORTALITY				6 HOUR MORTALITY			L TOTAL COSTS		
Emergency Response System Variables										
BASIC									−.173 (.049)	
E911		.649 (.150)				.319 (.153)			−.189 (.048)	
EMD		1.081 (.187)				.685 (.224)			.007 (.033)	
<i>Parametric Restrictions</i>	# Restrict	χ^2	<i>p</i> -value		# Restrict	χ^2	<i>p</i> -value	# Restrict	χ^2	<i>p</i> -value
BASIC = E911								1	.15	.699
Control Variables										
QUARTERLY DUMMIES	7	8.35	.303		7	16.19	.023	7	34.03	.000
INCIDENT TIME-OF-DAY DUMMIES	8	23.37	.003		8	28.83	.000	8	3.55	.000
PATIENT CHARACTERISTICS	9	49.91	.000		9	13.66	.135	9	5.42	.000
TIME-VARYING INCIDENT LOCATION CHARS.	8	10.14	.255		8	4.98	.759	8	3.08	.002
<i>R</i> ²									.417	
Adjusted <i>R</i> ²									.271	
Log-likelihood		−1,727.574				−389.646				
Number of observations		19,746				19,746			19,746	
Observations − Parameters		15,799				15,799			15,799	

^a 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.
^b Specification includes a fixed effect for each hospital/MCD combination.

outcome closely associated with longer-term survival, transfer to another hospital soon after the emergency incident is more ambiguous. Further, 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 focus on 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 , we distinguish between observations associated with (i) death at hour τ , prior to τ^F ; (ii) a transfer prior to τ^F (treated as right-censored); (iii) release to home prior to τ^F (treated as survival until τ^F);⁵² or (iv) survival and no discharge until τ^F . We present two Cox

⁵² Unlike patients with cancer or some other terminal illnesses, cardiac 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.

proportional hazard models (see, e.g., Cox (1972)) in Table 9 to highlight the main results. Formally, we estimate the following discrete-time hazard model, following the notation in (2), where ℓ_k is the identity of the hospital where patient k is admitted:

$$\begin{aligned} &\Pr(\text{Patient}(i, j, k, t) \text{ dies at hour } \tau \mid \text{Alive at hour } \tau - 1, \mathbf{s}_i^t, \mathbf{x}_k, \mathbf{z}_j^t, \ell_k) \\ &\equiv H(\tau \mid \mathbf{s}_i^t, \mathbf{x}_k, \mathbf{z}_j^t, \ell_k) = H_{j,\ell_k}(\tau) \cdot \exp \{q_t + E911_i^t(\alpha_{E911} - \alpha_{\text{NOT } E911}) + \mathbf{x}_k \boldsymbol{\beta} + \mathbf{z}_j^t \boldsymbol{\gamma}\}. \end{aligned} \quad (3)$$

We account for the existence of both patient heterogeneity, as well as heterogeneity across hospitals, by stratifying by the patient's hospital and MCD, allowing $H_{j,\ell}(\tau)$ to vary by hospital and MCD. No assumptions are required on the shape of each $H_{j,\ell}(\tau)$. With this specification, the coefficients are identified from variation within the hospital/MCD pair. 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 9; we report the Cox proportional hazard coefficients (i.e., we report $\tilde{\beta} = \exp\{\beta\}$, the proportional change in the hazard rate due to \mathbf{x} , so that a coefficient of one is associated with no change in the hazard). For both the 6-hour and 48-hour hazard models, 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). We could find no significant association between the mortality hazard and EMD adoption.

Both columns 1 and 2 assign N0 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 we stratify by MCD or MCD-hospital). Across all specifications, however, adoption of E911 lowers the hazard rate relative to NO 911 and BASIC taken together as a single category.

Consider the relationship between these results and our results about HINDEX (recall that E911 improved the average HINDEX by .04). As discussed in Section 3, the relationship between improvement measured at the time of ambulance arrival and improvement in 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 column 3 we consider a simple cost regression, including fixed effects for each MCD-hospital combination. Our results are thus identified by differences in the average cost of care after technology adoption among patients whose incidents occur in the same narrow geographic area and who receive treatment at the same hospital (our results are robust, however, to alternative control structures).⁵³ 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 that hospital

⁵³ 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.

outcome measures might have provided 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 incident severity or the reduced use of the “lights-and-siren” emergency response.

7. Implications and conclusions

■ The main contribution of this article 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, cardiac emergencies account for a small portion of calls handled by 911 centers. Cardiac emergencies make up less than 20% of all medical emergencies. Moreover, in at least one Pennsylvania county that maintains statistics, medical emergencies make up just 33% of all dispatched calls (a little over 50% require police, and the remainder require firefighters). 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.⁵⁴ The incremental costs of E911 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 6, 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,⁵⁵ 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 article highlights a general issue about productivity measurement in the service sector. Rather than attempting 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.

Appendix A

■ The following table contains the results from the health index probit regression used to construct HINDEX.

⁵⁴ 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.”

⁵⁵ Although the average patient in our sample is fairly healthy, the patients whose lives are saved by E911 are probably similar in health to AMI patients. Cutler et al. (2001) show that in 1994, AMI survivors had a life expectancy of 6 years, and they assign a quality weight of .74 for these patients.

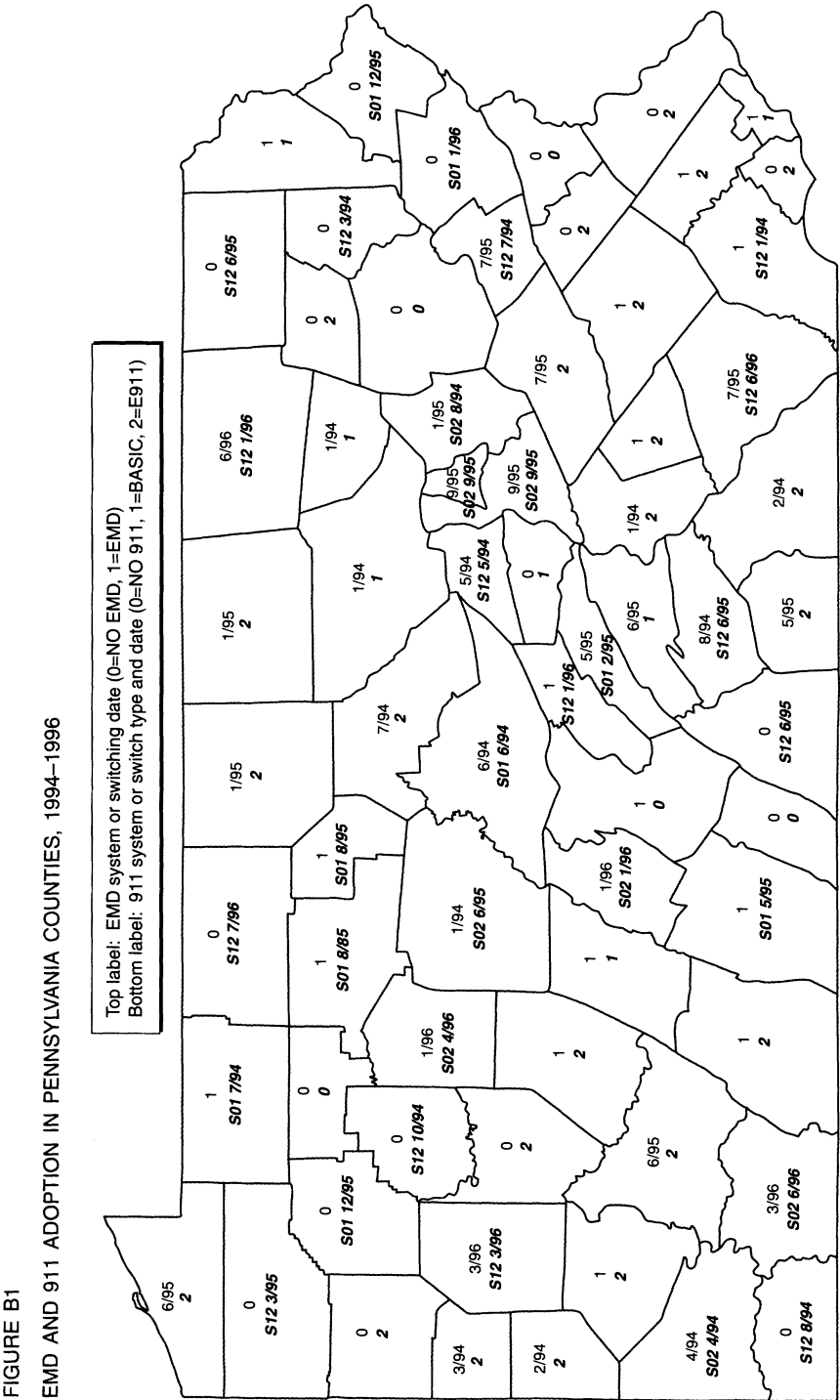
TABLE A1 **Health Index Probit Equation**
Dependent Variable = 48 HOUR MORTALITY

GLASGOW SCORE	HINDEX ^a
CAT1 ($4 \leq \text{Glasgow} \leq 5$)	-.359 (.293)
CAT2 ($6 \leq \text{Glasgow} \leq 8$)	-.180 (.191)
CAT3 ($9 \leq \text{Glasgow} \leq 12$)	-.351 (.170)
CAT4 ($13 \leq \text{Glasgow} \leq 15$)	-.835 (.137)
RESPIRATION	
CAT1 ($1 \leq \text{Resp} \leq 5$)	.505 (.260)
CAT2 ($6 \leq \text{Resp} \leq 9$)	-.337 (.267)
CAT3 ($30 \leq \text{Resp}$)	.568 (.176)
CAT4 ($10 \leq \text{Resp} \leq 29$)	.294 (.170)
BLOOD PRESSURE	
CAT1 ($1 \leq \text{Systol} \leq 49$)	-.052 (.442)
CAT2 ($50 \leq \text{Systol} \leq 75$)	-.012 (.145)
CAT3 ($76 \leq \text{Systol} \leq 89$)	-.040 (.136)
CAT4 (≥ 90)	-.801 (.115)
HIGH RISK PULSE	
HIGH RISK PULSE ($\text{Pulse} \leq 40$)	.265 (.110)
Pseudo R^2	.190
Number of observations	19,746
Log-likelihood	-2,412.971

^a Specification is based on the critical cutoff points identified in the clinical emergency medicine literature. Coefficients are probit coefficients.

Appendix B

■ The following figure illustrates the adoption behavior of Pennsylvania counties during the period 1994–1996.



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