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Electronic Trace Data and Legal Outcomes: The Effect of Electronic Medical Records on Malpractice Claim Resolution Time

Sam Ransbotham,[a] **Eric M. Overby,**[b] **Michael C. Jernigan**[c,d]

[a] Boston College, Chestnut Hill, Massachusetts 02467; [b] Georgia Institute of Technology, Atlanta, Georgia 30332; [c] Massachusetts General Hospital, Boston, Massachusetts 02114; [d] Harvard Medical School, Boston, Massachusetts 02115

Contact: sam.ransbotham@bc.edu, https://orcid.org/0000-0001-5305-035X (SR); eric.overby@scheller.gatech.edu, https://orcid.org/0000-0001-5285-4436 (EMO); mjernigan@partners.org (MCJ)

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Abstract. Information systems generate copious trace data about what individuals do and when they do it. Trace data may affect the resolution of lawsuits by, for example, changing the time needed for legal discovery. Trace data might speed resolution by clarifying what events happened when, or they might slow resolution by generating volumes of new and potentially irrelevant data that must be analyzed. To investigate this, we analyze the effect of electronic medical records (EMRs) on malpractice claim resolution time. Use of EMRs within hospitals at the time of the alleged malpractice is associated with a four-month (12%) reduction in resolution time. Because unresolved malpractice claims impose substantial costs on the entire healthcare system, our finding that EMRs are associated with faster resolution has broad welfare implications. Furthermore, as we increasingly digitize society, the ramifications of trace data on legal outcomes matter beyond the medical context.

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1. Introduction

Information systems generate and store large amounts of trace data: detailed data about what individuals and organizations do and when they do it. This data includes not only data that individuals generate in the form of documents, database entries, and social media updates (i.e., the "what"), but also metadata about system use, including when individuals log in and out, where individuals are located, and what device they use for access (i.e., the "when, where, and how"). Organizations increasingly use electronic trace data for many purposes, including profiling individuals for personalized marketing (e.g., Bleier and Eisenbeiss 2015) and assessing creditworthiness (e.g., Wei et al. 2015). Electronic trace data may also have important effects on the resolution of lawsuits by, for example, changing the time needed for discovery, which is the process through which each party obtains evidence from the other. Electronic trace data may provide detailed evidence about the chain of events leading up to an outcome. This trace data could increase or decrease the time to resolve lawsuits. On one hand, trace data may provide a clear and (mostly) incontrovertible account of what events happened when. A clearer account can help all parties in the lawsuit share and analyze the relevant evidence more quickly, leading to faster resolution. On the other hand, the sheer volume of trace data, including mountains of digital records that would not otherwise be available or searchable, may lengthen the process and thereby slow resolution.

We use the healthcare industry as the context to examine the tension between the potential clarity provided by trace data and the burden of analyzing it. Specifically, we analyze the relationship between the use of electronic medical records (EMRs) within hospitals and the time required to resolve medical malpractice claims filed against those hospitals. Healthcare is an important context for IT in general (e.g., Menon et al. 2000, Miller and Tucker 2009, Angst et al. 2010, Dranove et al. 2014), partly because of increasing use of EMRs and their potential effects on healthcare quality and cost. We focus on the effect of EMRs on malpractice claim resolution time for three reasons. First, EMRs generate trace data of the care administered (or not) to a patient, including when medical staff administered procedures, whether and when they ordered and reviewed test results, etc. These data could either speed or slow malpractice claim resolution, depending on whether they clarify or complicate the information needed for resolution. By examining this empirically, we extend our understanding of the effects of trace data on the resolution of lawsuits. Second, unresolved malpractice claims impose substantial economic and emotional costs on both providers and patients (Mello et al. 2010). Given this, policies or systems (such as EMRs) that affect claim resolution time have welfare implications. Indeed, multiple tort reform initiatives aim to expedite claim resolution (Kessler 2011). Given the limitations of tort reform, we take a fresh look at this issue by studying the potential of EMRs to expedite (or hinder) claim resolution. Finally, hospitals are increasingly implementing EMRs, spurred by incentive payments and penalties (authorized by the 2009 HITECH Act) and the promise of better patient care. However, it is critical for hospitals to understand how EMRs affect legal outcomes; indeed, malpractice "lawyers smell blood in electronic medical records" (Mearian 2015).

How does the use of EMRs within hospitals influence the resolution time of malpractice claims? To study this, we combine data on hospital-level EMR use with data on malpractice claim resolution. We analyze 7,411 resolved malpractice claims filed against 161 hospitals in Florida between 1999 and 2007. We collected data through December 2019, but we restricted analyses to claims originating no later than 2007 to allow sufficient time (~ 12 years) for them to resolve (as is necessary for any study of claim outcomes). We implement a variety of models to estimate the relationship between EMR use within hospitals and claim resolution time, controlling for potential confounders, such as claim severity, court system workload, hospital characteristics (e.g., size, case mix, and location), and time trends. Use of EMRs within hospitals at the time of the alleged malpractice is associated with a more than four-month (12%) reduction in claim resolution time. These results hold after accounting for potential endogeneity in a hospital's decision to implement EMRs. Additional exploratory analysis suggests that the mechanism by which EMRs affect resolution time is by speeding the discovery phase of the claim, particularly for claims that do not reach the lawsuit stage or that claimants abandon. In this setting, the benefits of the trace data recorded by EMRs outweigh the costs in terms of speeding resolution. Given the high emotional and economic costs of malpractice claims, faster resolution is likely to generate significant benefits for both patients and healthcare providers.

2. Literature Review and Motivation

Our analysis informs the growing body of research about the implications of electronic trace data for organizations and individuals. We focus on the implications of trace data for lawsuit resolution by studying how EMRs influence the resolution time of malpractice claims.

2.1. Electronic Trace Data, Electronic Discovery, and Lawsuit Resolution

Electronic trace data have implications for lawsuit resolution by, for example, affecting the time needed for discovery. Discovery, a process through which each party involved in a lawsuit obtains evidence from the other(s), usually includes depositions and requests for documents. In many jurisdictions, courts compel parties involved in the lawsuit, as well as others who are not directly involved but may have relevant information, to provide information. The speed of the discovery process can substantially affect how quickly a lawsuit resolves, as "the discovery phase is easily the most time consuming portion of most cases..." (HG.org 2016).

Electronic discovery refers to the aspect of the discovery process in which evidence results from electronic data, such as electronically stored documents, database entries, and other electronic trace data. For example, defense attorneys in a New York City lawsuit used trace data as an alibi when the murder suspect's public transit card (which showed where and when the suspect used subways and buses) provided evidence that the suspect was too far away from the crime scene to have been guilty (Chan 2008). As information systems and sensors (e.g., the Internet of Things) have become more pervasive, electronic discovery has become an increasingly large component of the overall discovery process.

Electronic trace data could either increase or decrease the time to resolve a lawsuit. Many of the actions, behaviors, etc., that electronic trace data capture would not otherwise be captured. As a result, electronic trace data adds to the overall volume of data that all parties must analyze during a lawsuit. Ceteris paribus, these additional data—and the time needed to analyze them—slow lawsuit resolution. Although voluminous electronic trace data require analysis, only a fraction of it may be relevant to the lawsuit. As an analogy, electronic data enlarge the size of the "haystack" (i.e., the overall volume of data), making it harder (and slower) to find the "needles" (i.e., the relevant data). On the other hand, legal professionals can often analyze electronic trace data more rapidly than data stored on paper precisely because it is in digital format. Electronic data often require less codification than do nonelectronic data (because the former are often coded when input), and the former are much easier to search, read, and understand than, for example, handwritten notes. The digital format should speed analysis, even of voluminous data (Cohendet and Meyer-Krahmer 2001).

Because capturing trace data in electronic form should yield an increase in both the amount of data and the rate at which legal professionals can analyze it, its effect on lawsuit resolution is unclear.

We summarize this tension as follows. Assume that the following equation defines the time required to resolve a lawsuit: Resolution time = [(data volume)/(analysis rate)] + (other factors), where "data volume" is the amount of data legal professionals must analyze during the lawsuit and "analysis rate" is the rate at which they can analyze those data. If the "volume" increase resulting from electronic trace data outpaces the corresponding "rate" increase, then resolution is slower. If the "rate" increase outpaces the "data" increase, then resolution is faster. Because which will occur is unclear a priori, how trace data affects lawsuit resolution is ultimately an empirical question.

2.2. Electronic Medical Records and Malpractice Claim Resolution Time

We examine the effect of electronic data, including trace data, on lawsuit resolution in the healthcare industry. The effect of electronic data—and information technology in general—on healthcare is an important and increasingly well-studied phenomenon. Information technology (including EMRs) can improve the care given to patients by increasing healthcare worker productivity, standardizing care practices, helping to ensure that these practices are followed, and reducing medical errors (Devaraj and Kohli 2000, Menon et al. 2000, Balas 2001, Dexter et al. 2001, Gray and Goldmann 2004, Hersh 2004, Koppel et al. 2005, Kuperman et al. 2007, Menon and Kohli 2013). However, there are challenges associated with the successful use of IT in healthcare. For example, the sensitive personal nature of the information within healthcare information systems exacerbates privacy concerns (Angst and Agarwal 2009, Miller and Tucker 2009), many providers complain that EMRs are cumbersome to use (McNickle 2011), and the productivity benefits of EMRs are unclear (Bhargava and Mishra 2014). Healthcare IT can also facilitate practices, such as aggressive billing, that may increase healthcare costs that are already considered too high (Sidorov 2006, Abelson et al. 2012, Soumerai and Koppel 2012, Curfman et al. 2013). Agarwal et al. (2010) and Kellermann and Jones (2013) review the effects of IT on healthcare quality, cost, and related outcomes.

We contribute to this stream of research—and also explore the implications of electronic trace data for lawsuit resolution—by examining the effect of EMRs on how long it takes to resolve medical malpractice claims. EMRs may affect malpractice claims in several ways, including not only how long it takes to resolve a claim, but also whether a patient files a claim at all and whether and to what degree the provider is liable. Regarding the likelihood of a patient filing a claim and the provider's subsequent liability, if EMRs improve quality of care, then they lower the likelihood that malpractice occurs and a patient files a claim (Studdert et al. 2006). However, EMRs may increase the discoverability of the care given to (or withheld from) patients by creating trace data that serves as an electronic paper trail, including the timing and sequence of care procedures (Mangalmurti et al. 2010). Although this can help defend malpractice claims if healthcare professionals properly administered care (Miller and Glusko 2003), it can serve as a "smoking gun" if they did not (Korin and Quattrone 2007). The electronic evidence could increase claim likelihood and liability for providers. Indeed, hospitals may be deferring IT investments because of the legal liability associated with electronic discovery of these trace data (Miller and Tucker 2014). Plaintiffs' attorneys, who "smell blood in electronic medical records" (Mearian 2015), have not overlooked this possibility. Given this concern, a small number of studies examine the link between EMR use and the likelihood of patients filing a malpractice claim. Two companion studies show a negative correlation between EMR use and malpractice claims (Virapongse et al. 2008, Quinn et al. 2012), and another shows no correlation (Victoroff et al. 2012). Although malpractice outcomes related to claim likelihood and liability are important, we focus our analysis on the effect of EMRs on claim resolution time. We do so for three reasons.

The first reason is that focusing on claim resolution time allows us to examine the tension between the potential clarity that electronic trace data provide and the burden of analyzing it. Malpractice claims take a long time to resolve for several reasons, including a lengthy discovery process in which the parties must gather and analyze data about whether the provider adhered to the appropriate standard of care as well as who was involved in the care that led to the injury (Seabury et al. 2013). EMRs generate several types of additional data that would not otherwise be available—or discoverable. We focus on three categories. First, EMRs produce metadata about when, how, and by whom a patient's medical records are created, accessed, and modified (Mangalmurti et al. 2010). These metadata can reveal which healthcare providers accessed a patient's EMR and when. One example of the use of EMR metadata in this way involved alleged malpractice by an anesthesiologist who recorded his postoperative notes minutes after an operation began rather than after the operation was complete (Vigoda and Lubarsky 2006). Claimants used this EMR metadata to allege that the anesthesiologist did not provide appropriate care. Without EMRs, this information would not be available for discovery. Second, healthcare providers use EMRs to communicate with each other about patient symptoms, plans of care, etc. (Joos et al. 2006). Because this communication is conducted (and likely recorded) electronically, it potentially becomes discoverable. Without EMRs, healthcare providers might be more likely to communicate face-to-face or via telephone, such that their communications would not be available for discovery. Third, EMRs provide a more complete record of patient care than paper-based records.[1] Records are more complete because of the additional data recorded in EMRs (including test results, images, past diagnoses, and treatment plans, etc.) and also because the data are legible (Hoffman and Podgurski 2009, Hoffman 2010). Without EMRs, less data would be available for discovery. Overall, these additional data may affect claim resolution time for the reasons discussed in the previous section. On one hand, the sheer volume of data—and the potential obligation of all parties to review it—might slow discovery and claim resolution (e.g., Degnan 2011). Indeed, producing data from EMRs for discovery is time-consuming because of the need to export and format the appropriate data, potentially in multiple ways given that different providers can access the EMR using different settings and configurations (Dimick 2010, Rush 2015). On the other hand, because the record of care given (or not) to the patient is electronic, parties involved in the claim may be able to analyze the relevant data and determine the claim's merits relatively quickly, leading to faster resolution. For example, if the EMR metadata or electronic communication files reveal a clear act of negligence (i.e., a smoking gun), then resolution could be relatively fast. Resolution might also be fast if the metadata show a series of log-ins and entries (including adding and/or viewing patient information, ordering tests, etc.) that are consistent with the applicable standard of care.

The second reason that we study resolution time is that medical malpractice claims create substantial monetary and emotional costs for providers and patients (Studdert et al. 2004, Mello et al. 2010). An important and often overlooked factor contributing to these costs is the time required to resolve claims. On average, physicians spend almost 11% of their career with an open, unresolved claim pending against them (Seabury et al. 2013). The long resolution time negatively affects healthcare providers by increasing stress, distracting them from the practice of medicine, and delaying their ability to implement changes to prevent future medical errors (Sage 2004, Studdert et al. 2004, Seabury et al. 2013). Nearly half of physicians sued for malpractice have claims last three years or longer with one physician complaining about "years of agonizing about the potential for a catastrophic outcome, loss of license, practice, etc." (Peckham 2015); more than 95% of physicians sued for malpractice found the experience "unpleasant," "upsetting," "very bad," or "horrible." Long resolution times also increase the uncertainty malpractice insurers face about their risk exposure, leading to fluctuations in insurance premiums that further disadvantage providers (Government Accountability Office 2003). Long resolution times negatively affect patients through increased anxiety, lack of closure with the provider, and delays in receiving appropriate compensation (Gallagher and Levinson 2005, Hobgood et al. 2005). Although many analysts agree on the negative consequences of the malpractice system, most focus on tort reform as the method to ameliorate these issues (Thorpe 2004). For example, possible reforms that would affect claim resolution time include adjusting the statute of limitations for filing a claim and creating specialized "health courts" that could handle claims more efficiently than the standard court system (Chodos 2015). However, the significant pessimism about the potential for tort reform to provide relief (Mello et al. 2003) suggests investigating other methods. Accordingly, we study the potential of EMRs to expedite (or hinder) claim resolution. EMRs may help improve the malpractice system because "excellent documentation is the backbone of defensive medicine" (Gart 2008), and one of the key pieces of advice from physicians who have been sued is to "document, document, document" (Peckham 2015).

Third, hospital adoption of EMRs is increasing steadily, and much research investigates their effects on quality of patient care, healthcare costs, physician and patient satisfaction, etc. However, relatively little research considers the relationship between EMRs and healthcare litigation, and none focuses on EMRs and malpractice claim resolution time. Given the potentially large welfare implications associated with speeding up malpractice claim resolution, understanding how EMRs relate to claim resolution time is an important policy issue.

3. Data, Study Period, and Empirical Approach

3.1. Data Sources

Because malpractice claims take years to resolve, assessing the relationship between EMRs and claim resolution time has only recently become feasible. This lag may explain the lack of empirical research on this topic. Another reason for the lack of research is that there is no consolidated, multiprovider data repository suitable for studying the relationship between EMRs and claim resolution time (Institute of Medicine 2011). To overcome this, we constructed a new data set by consolidating data from the sources described as follows. We focus on the state of Florida because of the availability of detailed claim data.

3.1.1. Malpractice Claims. The state of Florida requires licensed medical malpractice insurance providers to report on resolved malpractice claims, pursuant to reporting statute Chapter 627.912, F.S. These data are public record and are available through the Florida Office of Insurance Regulation.[2] We downloaded data for the claims filed against hospitals through December 2019. Plaintiffs can file claims against hospitals and/or individual healthcare providers. We limit our analysis to claims against hospitals, some of which name other defendants in addition to the hospital. We do this because our measure of EMR use is at the hospital level (as discussed); we do not observe EMR use at the individual provider level. Because insurers do not report claims until resolved, we limit our analysis to claims filed between 1999 and 2007. This lag allows at least 12 years for claims to be resolved and reported as is necessary for any study of claim outcomes. A 12-year lag is a longer (i.e., more conservative) window than that typically used in studies of claim outcomes (Virapongse et al. 2008, Quinn et al. 2012). We justify the (at least) 12-year lag as follows.

3.1.2. Use of EMRs Within Hospitals. The Healthcare Information and Management Systems Society (HIMSS) conducts annual surveys of hospital chief information officers and information systems managers about the use of information technology, such as EMRs (Healthcare Information and Management Systems Society 2013). These established measures of EMR use predate the emerging meaningful use standard (Angst et al. 2011, 2010; Dranove et al. 2014). As shown in Table 1, HIMSS considers EMRs to include multiple component systems and considers each hospital to be in one of seven stages of EMR use each year based on the component systems at the hospital (Healthcare Information and Management Systems Society 2015).

Table 1. HIMSS U.S. EMR Adoption Model

Stage	System capabilities (cumulative)
Stage 7	Complete EMR; continuity of care document transactions to share data; data warehousing; data continuity with emergency department, ambulatory, outpatient
Stage 6	Physician documentation (structured templates), full clinical decision support system (variance & compliance), full radiology picture archiving and communication system
Stage 5	Closed-loop medication administration
Stage 4	Computerized practitioner order entry, clinical decision support (clinical protocols)
Stage 3	Nursing/clinical documentation (flow sheets), clinical decision support system (error checking), picture archiving and communication system available outside radiology
Stage 2	Clinical data repository fed by ancillaries, controlled medical vocabulary, clinical decision support, may have document imaging; health information exchange capable
Stage 1	Ancillaries (laboratory, radiology, pharmacy) all installed
Stage 0	All three stage 1 ancillaries (laboratory, radiology, pharmacy) not installed

Source. Healthcare Information and Management Systems Society (2015).

Because of the limited number of hospitals in each of the seven stages and to be consistent with other research (e.g., Dranove et al. 2014), we dichotomize hospitals as having either basic (stage 1 through stage 3) or advanced (stage 4 through stage 7) EMR functionality in each year of the study period. (Although our basic and advanced categories are similar to those used by Dranove et al. (2014), they do not base their categories on the HIMSS EMR adoption model.) Basic EMR functionality includes a clinical data repository fed by ancillary clinical systems, electronic clinical documentation for at least one inpatient service (flow sheets), availability of electronic images beyond the radiology department, and basic clinical decision support. Advanced EMR functionality includes computerized order entry; advanced decision support, such as variance/compliance tracking; and physician documentation systems.

3.1.3. Other Hospital Characteristics. The state of Florida requires healthcare facilities within the state to report information annually to the Florida Agency for Healthcare Information. The reports that this agency publishes provide annual data on hospital size, patient population, operations, and finances.

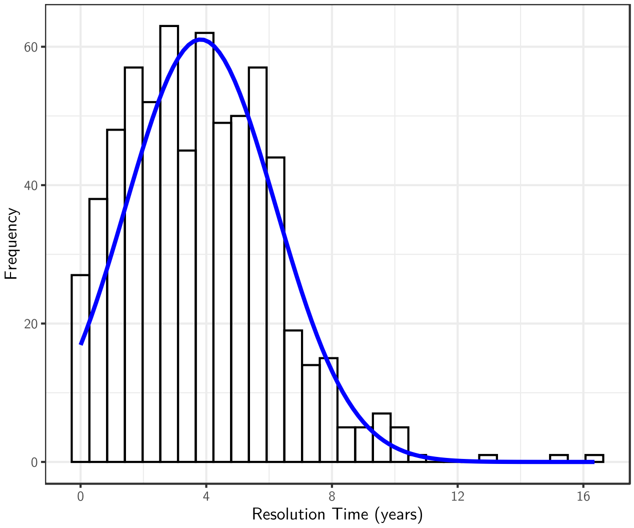
Matching data across these sources yields a sample of 7,411 resolved claims filed against 161 hospitals.

3.2. Variables

3.2.1. Claim Resolution Time. The dependent variable is the length of time required to resolve the claim (*Resolution Time*), measured as the number of days from the date the injury occurred to the date the claim was resolved, each of which the malpractice claim data records. Figure 1 depicts the distribution of resolution times of the claims originating in 1999. Nearly 100% of claims from 1999 were resolved within 12 years with a nontrivial number of those being resolved in years 9, 10, and 11. The distribution of resolution times suggests that allowing at least 12 years (but not fewer) for claims to be resolved and reported is appropriate.

3.2.2. Other Claim Characteristics. The malpractice claim data records several other variables. *Severity* describes the extent of the patient's injury. *Resolution Stage* indicates the stage at which the claim was resolved. Table 2 lists the *Severity* and *Resolution Stage* categories. *Claim Defendants* is the number of defendants the claim lists; claims against more defendants may require increased coordination and more time to resolve. *Monetary Size* is the total amount paid (if any)

Figure 1. (Color online) Histogram of Resolution Time of Malpractice Claims Originating in 1999



for the claim (in thousands of U.S. dollars), which includes indemnity payments and loss adjustment expenses. This proxies for the complexity of the claim. *Claim Load* is the number of malpractice claims open at the same time and within the same court system (i.e., county) as the focal claim. The case workload within the system could influence the resolution time of the focal claim. We also created an analogous measure of the number of simultaneously open claims against the focal hospital (as opposed to within the hospital's county).

3.2.3. Use of EMRs Within Hospitals. Our focal explanatory variable is whether a hospital used EMRs when the injury occurred, which means that an electronic system was available to capture data related to the care associated with the injury. *Basic EMR* indicates whether a hospital had systems that provide basic EMR functionality at the time of the injury. *Advanced EMR* indicates whether a hospital had systems that provide advanced EMR functionality at the time of the injury. (Our coding is such that when *Advanced EMR* = 1, *Basic EMR* = 0.) Section 3.1.2 describes how we coded basic versus advanced EMR functionality. Table 3 illustrates how these variables change across years for hospitals as they adopt EMRs.

3.2.4. Other Hospital Characteristics. Data from the Florida Agency for Healthcare Information controls for characteristics of the hospitals that may affect resolution time. We control for size using *Employees*, measured as the number of full-time equivalent (FTE) employees at the hospital in each year. *Employees* is highly and positively correlated with other measures of hospital size, such as number of physicians, number of beds, number of staffed beds, number of visits, etc. Because of the collinearity among these variables, we include only *Employees* in the models; however, the results are robust to alternative measures of size. *Working Hours per Patient* controls for (the inverse of) the utilization level of the hospital staff. We measure this as the total number of working hours available from the hospital employees divided by the patient load (measured in adjusted patient days) in each year. *Salary per FTE* is the average compensation per full-time equivalent employee at the hospital in each year; this variable partially controls for the mix of staff (e.g., physicians, technicians) at a hospital. *Net Revenue per Patient* is the net operating revenue of the hospital divided by the patient load (measured in adjusted patient days) in each year. This variable controls for aspects of the hospital's financial condition. *Occupancy* is the average percentage of beds that were in use throughout the year and helps control for utilization level of the hospital. *Geographic Index* measures the variation in cost and services attributable to market conditions in a region. An index below 100 indicates that a hospital's charges for services are lower than the state average in a given year. This variable helps control for aspects of the hospital's cost structure. *Case Mix Index* is a diagnosis-weighted average of the patients that the hospital treats in each year and controls for the underlying population the hospital serves. All dollar amounts are adjusted to January 2000 equivalents using the Consumer Price Index as reported by the U.S. Bureau of Labor Statistics.

Table 2 provides descriptive statistics for the sample; Table 4 provides correlations.

3.3. Suitability of the Study Period

As the Literature Review and Motivation section (Section 2) discusses, EMRs create data (including metadata, electronic communication records, and more complete patient records) that would not otherwise be available and that could speed or slow claim resolution. It is important to consider whether EMRs used by Florida hospitals during the 1999–2007 study period generated this type of additional data given that EMRs were nascent during this period. We conclude that they did. First, EMRs during the study period produced metadata. In 2000, 25 of the 28 EMR systems surveyed generated audit trails of access to the system, which legal professionals could use to determine whether and when a provider accessed or updated the EMR (Rehm and Kraft 2001). Second, EMRs during the study period facilitated (and, by extension, recorded) electronic communication between healthcare providers. Indeed, healthcare providers identified electronic communication as one of the key benefits of EMRs during the study period (Miller and Sim 2004, Joos et al. 2006) and EMR vendors (Rehm and Kraft 2001)

Table 2. Descriptive Statistics

Variable	Minimum	Maximum	Mean	Median	Standard deviation
Claim variables					
Resolution Time (days)	1	6,770	1,188.71	1,015	844.23
Monetary Size (US$K)	0	73,813	329.20	58	1,548.25
Claim Defendants (count)	1	40	2.00	1	2.18
Claim Load (count)	0	3,247	353.95	57	495.73
Resolution Stage					
Abandon: Claim or suit abandoned	0	1	0.204	0	0.403
Presuit: Settlement reached prior to presuit period	0	1	0.047	0	0.212
Presuit: Within the presuit period	0	1	0.192	0	0.394
Presuit: After arbitration is initiated or prior to suit being filed	0	1	0.045	0	0.208
Pretrial: Within 90 days of suit being filed	0	1	0.020	0	0.141
Pretrial: After suit filed; prior to/during settlement conference	0	1	0.473	0	0.499
Trial: During trial, but before court verdict	0	1	0.006	0	0.075
Trial: After court verdict	0	1	0.008	0	0.089
Trial: After notice of appeal is filed	0	1	0.001	0	0.031
Trial: During appeal	0	1	0.001	0	0.035
Trial: After appeal	0	1	0.003	0	0.053
Severity					
Emotional	0	1	0.073	0	0.259
Slight	0	1	0.046	0	0.210
Minor Temporary	0	1	0.240	0	0.427
Major Temporary	0	1	0.123	0	0.328
Minor Permanent	0	1	0.080	0	0.271
Significant Permanent	0	1	0.072	0	0.259
Major Permanent	0	1	0.061	0	0.240
Grave Permanent	0	1	0.033	0	0.179
Death	0	1	0.272	0	0.445
Hospital variables					
Employees (full-time equivalents)	27.800	26,776.200	1894.628	1064.000	2242.469
Working Hours per Patient (hours / patient days)	1.870	176.550	24.273	23.090	5.593
Salary per FTE (US$K)	6.218	65.813	45.043	44.815	6.407
Net Revenue per Patient (US$K / patient days)	0.024	3.042	1.462	1.435	0.329
Occupancy (percentage)	0.020	1.043	0.602	0.611	0.138
Geographic Index (index)	64.150	107.690	101.333	101.920	4.029
Case Mix Index (index)	0.492	2.034	1.336	1.326	0.202
Basic EMR (one if in use)	0	1	0.583	1	0.493
Advanced EMR (one if in use)	0	1	0.309	0	0.462

Notes. The unit of analysis is the malpractice claim; 7,411 observations. For hospital variables (e.g., *Employees*, *Occupancy*, etc.), we use the value for the hospital in the year the injury occurred. We adjust all dollar amounts to January 2000 equivalents using the Consumer Price Index as reported by the U.S. Bureau of Labor Statistics.

widely supported these features. Third, commentators remarked on the completeness of EMRs during this period. For example, Miller and Sim (2004, pp. 118–119) describe how even basic use of EMRs "increased completeness of documentation" and "improved the legibility and accessibility of progress notes and increased the availability of electronic problem and allergy lists." Additionally, the subheading of the discussion of EMRs and malpractice liability by Korin and Quattrone (2007) reads "Electronic health records contain more information about patients than their paper counterparts. . ."

Physicians or other caregivers may not have widely used EMRs during this era even if the hospitals themselves implemented EMRs. However, EMR metadata would reflect any such nonuse, which could affect claim resolution. For example, suppose that a physician who used EMRs only sporadically failed to consult the EMR at a critical time, such as to review a test result or image posted to the EMR. EMR metadata would likely chronicle that error of omission; this evidence would not exist if the hospital did not have EMRs.

3.4. Empirical Approach

We investigate whether the use of EMRs within a hospital influences the resolution time for malpractice claims filed against that hospital. We analyze claims filed against all hospitals in the data, which we refer to as the "all hospitals" analysis ($n = 7,411$) as well as claims filed against only those hospitals that adopted EMRs during the sample period, which we refer to as the "adopting hospitals" analysis ($n = 2,044$).

Table 3. Changes in EMR Use Within Hospitals from 1999 to 2007

	EMR at end			
	None	Basic	Advanced	Total at start
EMR at start				
None	7	12	53	72
Basic	0	26	50	76
Advanced	0	0	13	13
Total at end	7	38	116	161

Notes. The matrix depicts hospitals based on their EMR use at the beginning and end of the sample period. Each cell represents a count of hospitals. For example, the None–None cell indicates that seven hospitals never had EMRs during the sample period; the None–Basic cell indicates that 12 hospitals had no EMRs at the beginning of the period and basic EMRs at the end, etc.

The adopting hospitals subsample excludes hospitals that never had EMRs during the sample period as well as those that always had EMRs.

We begin with a model-free comparison of means and medians. Next, we use multiple regression to control for factors other than EMRs that prior research indicates might influence claim resolution time. We use a difference-in-differences approach in which we take advantage of variation in which hospitals adopt as well as when they adopt. The difference-in-differences analysis is estimable not only for the all hospitals subsample, but also for the adopting hospitals subsample because hospitals adopted EMRs at different times. To illustrate this, assume that hospital A adopted in 2003 and hospital B adopted in 2004. The difference between resolution times between 2002 and 2003 for hospital A (which is treated during this period) contrasts the difference between 2002 and 2003 for hospital B (which serves as a control during this period). Year indicator variables (i.e., fixed effects) account for macrolevel changes in the healthcare and legal environments that might influence resolution times. For example, the state of Florida enacted statute 766.118 in 2003 to limit noneconomic damages that courts could award to a patient; the indicator variables for 2003–2007 capture the effect that the passage of this law might have on claim resolution times. Year indicator variables are an important part of our identification strategy as they account for many unobserved factors that manifest over time. We used ordinary least squares regression because the dependent variable, *Resolution Time*, although an integer, has a mean much greater than zero and an approximately normal distribution (see Figure 1). Later robustness tests consider alternative approaches.

Our focal model is

$$t_{jky} = \beta_0 + \beta_b Basic_{jy} + \beta_a Advanced_{jy} + \beta_{h1} Hospital_j + \beta_{h2} Hospital_{jy} + \beta_c Claim_k + \beta_y Year_y + \epsilon_{jky}, \quad (1)$$

where t_{jky} is the *Resolution Time* for claim k against hospital j in year y; $Basic_{jy}$ ($Advanced_{jy}$) indicates if hospital j used basic (advanced) EMRs in year y; $Hospital_j$ are hospital fixed effects that control for all time-invariant hospital characteristics; $Hospital_{jy}$ is a vector containing time-varying hospital characteristics that describe hospital j in year y (e.g., *Employees*); $Claim_k$ is a vector of covariates for claim k; $Year_y$ are yearly indicator variables (i.e., fixed effects) that reflect when the plaintiff filed the claim; ϵ_{jky} is an error term clustered by hospital so that we avoid understating the standard errors (Bertrand et al. 2004); and βs estimate intercepts and coefficients.

We did not randomly assign EMRs to hospitals; rather, the use of EMRs is a strategic choice made by each hospital. If we ignore the potential endogeneity this creates, then our estimate of the relationship between EMRs and claim resolution time may reflect the possibility that hospitals with EMRs have characteristics that

Table 4. Correlations

	Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
1	*Resolution Time*	1											
2	*Severity*	0.07	1										
3	*Employees* (ln)	0.11	0.02	1									
4	*Working Hours per Patient*	0.08	0.01	0.60	1								
5	*Salary per FTE*	−0.07	−0.01	0.14	−0.15	1							
6	*Net Revenue per Patient*	−0.18	−0.02	0.18	0.17	0.43	1						
7	*Occupancy*	−0.03	0.03	0.25	−0.08	0.13	0.20	1					
8	*Geographic Index*	0.11	0.01	0.23	−0.03	0.27	−0.02	0.04	1				
9	*Case Mix Index*	−0.03	−0.05	0.36	0.29	0.05	0.50	0.11	0.00	1			
10	*Claim Load*	0.59	0.16	0.12	0.08	−0.11	−0.18	−0.02	0.21	−0.01	1		
11	*Monetary Size*	0.10	0.14	0.05	0.04	−0.01	0.00	0.02	0.02	0.01	0.12	1	
12	*Claim Defendants* (ln)	0.25	0.34	0.00	−0.03	−0.12	−0.13	0.00	0.05	−0.08	0.40	0.11	1
13	*EMR*	0.02	−0.09	0.01	−0.15	0.33	0.20	0.01	−0.06	−0.04	−0.06	−0.02	−0.04

Notes. Pearson product moment correlations. The unit of analysis is the malpractice claim: 7,411 observations. For variables measured at the hospital/year level, we use the value for the hospital in the year the injury occurred. To assess correlation, we code *EMR* as zero for none, one for basic, and two for advanced; we code *Severity* as an integer corresponding to increasing severity based on the order shown in Table 2.

inherently lead to shorter (or longer) claim resolution time rather than capturing a more direct relationship. Examples of such characteristics include a hospital's size and case mix, which may affect the number and type of malpractice claims that a hospital handles as well as the resources available to handle them (thereby affecting claim resolution time) and may also correlate with EMR use. A related potential issue would arise if hospitals that implement EMRs always resolve claims faster than average. If this were the case, then EMRs would be associated with faster resolution times, but not in a direct way. We address these potential endogeneity issues in four ways.

First, we explicitly control for hospital characteristics that influence a hospital's choice to use EMRs and claim resolution time. For example, our regressions include a rich set of time-variant hospital covariates (such as hospital size) as well as hospital fixed effects that control for time-invariant hospital characteristics, such as profit/nonprofit and location, many of which are associated with EMR use (Kazley and Ozcan 2007, Simon et al. 2007, Angst et al. 2010, Dranove et al. 2014). Second, hospitals that adopted EMRs during the sample period may systematically differ from those that did not in ways that lead to faster or slower claim resolution. In light of this, we replicate our analyses using only the adopting hospitals subsample. As shown, results are similar, thereby mitigating this concern. Third, we conduct a timing falsification check using leading and lagging indicator variables of EMR use. These indicators allow us to verify that the speed benefits that we attribute to EMRs do not appear until after EMR use begins, limiting the possibility that the hospitals that implemented EMRs always had faster than average resolution times. Fourth, we match claims filed against hospitals with EMRs to those against hospitals without EMRs. We use this matched sample to corroborate our main results as well as to conduct a sensitivity test (Rosenbaum 2002, 2005) to assess how large an effect any unobserved confounding variables would need to have to change our conclusions.

We also conduct several robustness checks, including estimating a multilevel model that includes random intercepts for each hospital, using count models, excluding the EMR implementation year from the analysis, mitigating the potential effect of outliers by removing claims filed against large hospitals (as measured by the number of claims and number of employees), and using a hospital-level version of the *Claim Load* variable.

4. Results

4.1. Preliminary, Model-Free Evidence

First, Table 5 explores the relationship between EMRs and claim resolution time through unadjusted comparison of means (t-tests) and medians (Mann–Whitney signed rank tests). We focus on median comparisons because they are more robust to potential outliers. Claims filed against hospitals that did not have EMRs in the year of the alleged malpractice had a median resolution time of 1,237 days. In hospitals that had basic EMR functionality in the year of the alleged malpractice, the median resolution time was 978 days.

Table 5. EMRs and Malpractice Claim Resolution Time: Comparison of Means and Medians

All hospitals (161 hospitals, 7,411 claims)					
Variables	n	Mean	Standard deviation	Median	
No EMR	801	1,350.87	788.67	1,237	
Basic EMR	4321	1,111.67	754.38	978	
Advanced EMR	2,289	1,277.38	993.98	1,009	
Differences		Δ Mean	t	Δ Median	$W(\times 10^3)$
Basic EMR minus No EMR		−239.199***	−7.94	−259***	2,072
Advanced EMR minus Basic EMR		165.709***	6.98	31***	4,709
Advanced EMR minus No EMR		−73.490*	−2.11	−228***	1,039
Adopting hospitals (65 hospitals, 2,044 claims)					
Variables	n	Mean	Standard deviation	Median	
No EMR	671	1,368.82	777.40	1,256	
Basic EMR	598	1,282.81	834.58	1,119	
Advanced EMR	775	965.68	627.67	841	
Differences		Δ Mean	t	Δ Median	$W(\times 10^3)$
Basic EMR minus No EMR		−86.01	1.893	−137**	220
Advanced EMR minus Basic EMR		−317.13***	7.753	−278***	288
Advanced EMR minus No EMR		−403.14***	10.74	−415***	346

Note. Mean (t-tests) and median (Mann–Whitney signed rank tests) comparison of claim resolution time by degree of EMR functionality: none, basic, or advanced.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

This represents a 21% speed improvement ($p < 0.001$). In hospitals that had advanced EMR functionality in the year of the alleged malpractice, the median resolution time was 1,009 days, which is 18% faster than "no EMR" ($p < 0.05$). We replicated this analysis using only the adopting hospitals subsample (lower panel of Table 5). Median resolution times were 11% and 33% faster for claims filed in years in which the hospital had basic and advanced EMR functionality (respectively) versus no EMR. The adopting hospital result suggests that hospitals' claim resolution times decrease after they adopt EMRs.

4.2. Focal Analysis

Table 6 shows the results of the difference-in-differences analysis (Equation (1)) using the all hospitals sample and the adopting hospitals subsample. In all models, EMRs are associated with a reduction in claim resolution time. For the all hospitals analysis (Model 1), basic EMRs are associated with a 141-day reduction ($\beta = -141.12$, $p < 0.001$), which represents a 12% decrease from the mean. Advanced EMRs are associated with a 251-day reduction (i.e., $\beta = -250.93$, $p < 0.001$), which represents a 22% decrease. The advanced EMR coefficient is statistically different from the basic EMR coefficient ($p < 0.001$). Results from the adopting hospitals analysis (Model 2) are similar: $\beta = -256.55$ ($p < 0.001$) for basic EMRs and $\beta = -454.62$ ($p < 0.001$) for advanced EMRs.

The finding that advanced EMRs are associated with a greater reduction compared with basic EMRs supports a direct link between EMRs and claim resolution time. If our results were simply a result of hospitals that use EMRs having inherent (and unobserved) characteristics that lead to faster claim resolution, then the coefficients for basic and advanced EMRs would be less likely to differ.

4.2.1. Timing Falsification Check. To examine the validity of our difference-in-differences approach, we adjust our focal model to include leading and lagged indicator variables (e.g., Autor 2003) that reflect how many years before or after a hospital began using basic EMRs that each injury occurred. For example, suppose that a hospital began using basic EMRs in 2003. Then, *Basic* EMR_{t-2} equals one for claims against that hospital in which the injury occurred in 2001 and zero otherwise; *Basic* EMR_{t+1} equals one for claims against that hospital in which the injury occurred in 2004 and zero otherwise, etc. The *Basic* EMR_{t-4} and *Basic* EMR_{t+4} terms are inclusive of all years preceding and following. For example, *Basic* EMR_{t-4} equals one for claims against EMR-adopting hospitals in which the injury occurred four or more years before adoption. To avoid the "dummy variable trap," we withheld the *Basic* EMR_{t-1} indicator from the model. In Model 3 in Table 6, the coefficients for *Basic* EMR_{t-4}, *Basic* EMR_{t-3}, *Basic* EMR_{t-2}, and *Basic* EMR_t are not statistically distinguishable from the base case (*Basic* EMR_{t-1}). The other coefficients show that the association between EMRs and resolution time does not appear until one year after initial EMR implementation and (generally) gets larger (i.e., more negative) each year. The timing suggests that EMR use triggers faster resolution times as opposed to being triggered by an unobserved factor correlated with and preceding a hospital's decision to implement EMRs. The lack of significance for the *Basic* EMR_t coefficient may be because EMRs are in use for only a portion of the implementation year (i.e., we do not know the exact date EMR use began within the year); as such, some injuries in the implementation year may occur before EMRs were in use. We limit this model to basic EMRs because many hospitals transition from basic EMRs to advanced EMRs. Including indicator variables for *Advanced* EMR_{t-2}, ..., *Advanced* EMR_{t+6} would introduce collinearity. For example, if a hospital transitioned to advanced EMRs two years after implementing basic EMRs, then *Advanced* EMR_{t-2} would be perfectly collinear with *Basic* EMR_t such that we could not estimate both of their coefficients. Indeed, the finding that the coefficients get larger year over year may be because hospitals transition to advanced EMRs. For example, if hospitals implement advanced EMRs two years after basic EMRs, then the *Basic* EMR_{t+3} coefficient would pick up the effect of *Advanced* EMR_{t+1}. Figure 2 illustrates the lead and lag estimates.

4.2.2. Extending the Sample Time Period. We extended the sample period to include claims filed as late as 2011. Results are similar: $\beta = -109.88$ ($p < 0.01$) for basic EMRs and $\beta = -231.58$ ($p < 0.001$) for advanced EMRs. We do not use the 1999–2011 period for the main sample because some claims from 2008–2011 may still be unresolved (and, thus, not reported) as discussed. These missing data could bias our results. However, the consistency across results suggests that the effect may hold for newer EMR systems (at least those through 2011).

4.2.3. Sensitivity Analysis. Despite this analysis, it remains possible that unobserved hospital characteristics correlate with both faster claim resolution and EMR use. If that were the case, then faster resolution might be attributable to these unobserved confounders and not to EMRs. A Rosenbaum sensitivity analysis quantifies how influential these unobserved confounders would have to be to alter our conclusion (Rosenbaum 2002). To conduct this analysis, we first generated a matched sample of claims filed against hospitals with at least basic EMR functionality at the time of injury (i.e., "treated" claims)

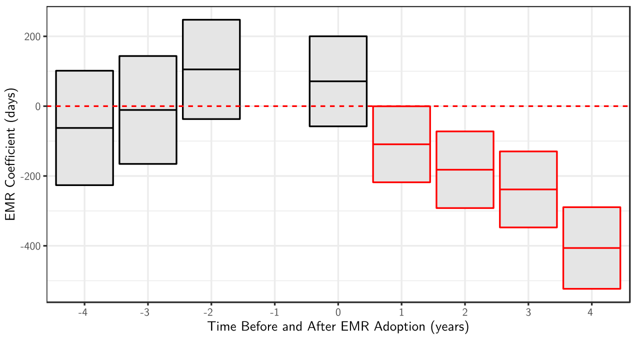
Table 6. EMRs and Malpractice Claim Resolution Time

	All hospitals	All hospitals	Adopting hospitals	All hospitals	All hospitals
	Control			Leads/lags	Through 2011
Variables	Model 0	Model 1	Model 2	Model 3	Model 4
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	Yes
Severity indicators	Yes	Yes	Yes	Yes	Yes
Constant	1,699.498*	1,383.867*	1,312.941	2,085.570**	303.293
	(682.852)	(676.059)	(1,895.251)	(695.119)	(549.542)
Claim Load (ln)	114.649***	114.097***	111.851***	112.966***	117.357***
	(2.719)	(2.715)	(4.918)	(2.709)	(2.324)
Employees (ln)	−239.457***	−206.885***	−183.228	−250.641***	−121.683**
	(59.389)	(58.466)	(176.193)	(57.922)	(47.109)
Working Hours per Patient (std)	4.227	5.005	−15.560	−2.699	111.343***
	(16.274)	(16.946)	(24.745)	(16.146)	(13.654)
Salary per FTE (std)	−376.965***	−365.614***	−311.702***	−349.606***	−365.300***
	(25.610)	(25.826)	(41.423)	(26.035)	(25.591)
Net Revenue per Patient (std)	−134.368***	−118.733***	−62.379	−90.910***	−115.772***
	(21.082)	(21.010)	(33.446)	(20.593)	(18.997)
Occupancy (std)	46.865*	47.844*	−4.758	59.341**	54.421***
	(19.913)	(19.793)	(43.257)	(19.835)	(15.070)
Geographic Index	−0.249	0.434	−8.690	−2.482	5.740
	(3.987)	(3.966)	(8.297)	(3.993)	(3.427)
Case Mix Index	246.839	283.671*	811.254***	219.849	176.127
	(127.297)	(126.653)	(200.478)	(130.963)	(117.480)
Claim Defendants (count, log)	60.263***	58.526***	36.543	58.254***	65.846***
	(13.811)	(13.802)	(28.271)	(13.768)	(11.313)
Monetary Size (/1000 $)	0.019**	0.020**	−0.008	0.020**	0.002
	(0.007)	(0.007)	(0.007)	(0.007)	(0.003)
Basic EMR		−141.123***	−256.546***		−109.883**
		(38.864)	(46.747)		(36.210)
Advanced EMR		−250.928***	−454.617***		−231.576***
		(40.921)	(58.100)		(38.504)
Basic EMR_{t-4}				−62.422	
				(83.620)	
Basic EMR_{t-3}				−10.913	
				(78.843)	
Basic EMR_{t-2}				105.250	
				(72.563)	
Basic EMR_{t}				71.196	
				(65.816)	
Basic EMR_{t+1}				−109.198*	
				(55.542)	
Basic EMR_{t+2}				−182.096**	
				(56.018)	
Basic EMR_{t+3}				−238.516***	
				(55.547)	
Basic EMR_{t+4}				−406.278***	
				(59.646)	
Observations	7,411	7,411	2,044	7,411	10,123
R^2	0.604	0.606	0.497	0.611	0.580
F statistic	56.323***	56.327***	24.237***	55.742***	68.732***

Notes. Ordinary least squares regression on claim resolution time (measured in number of days since injury). Standard errors clustered by hospital; (std) indicates standardized variables.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Figure 2. (Color online) EMR Use and Resolution Time: Leads and Lags Model



Note. The figure illustrates the lead and lag coefficients for *Basic EMR* shown in Table 6; 95% confidence interval shaded.

and those without EMR functionality at the time of injury (i.e., "control" claims). We conducted one-to-one matching and used multivariate matching with a genetic search algorithm that determines the optimal weight for each covariate (Diamond and Sekhon 2012). We matched claims based on *Claim Load*, *Severity*, *Employees*, *Working Hours per Patient*, *Salary per FTE*, *Net Revenue per Patient*, *Geographic Index*, *Case Mix Index*, *Monetary Size*, and *Claim Defendants*. Table 7 describes the results of the matching process by providing the mean values for each variable before and after the matching. (We exclude *Occupancy* from the analysis because the balance for this variable gets substantially worse after matching although the results are consistent if we include *Occupancy* in the matching.)

After matching, we compared *Resolution Time* between treated and control claims. Based on a mean comparison *t*-test, *Resolution Time* was 152 days faster for treated claims ($p < 0.01$). The objective of Rosenbaum sensitivity analysis is to quantify how much of an effect unobserved confounders would need to have to overturn our conclusion of a significant difference between treated and control claims. We used Wilcoxon's signed rank test for matched pairs to perform the sensitivity analysis (Rosenbaum 2005). To attribute the faster resolution time to unobserved confounders, they would need to (a) be highly correlated with faster resolution, and (b) increase the odds of the claimed-against hospital having EMRs by a factor of 1.86 (i.e., $\Gamma = 1.86$ in sensitivity analysis notation). Although there is no consensus about the appropriate size for Γ in social science research, $\Gamma = 1.5$ indicates substantial insensitivity, and $\Gamma = 1.2$ is around average (Sen 2014).

4.3. Alternative Analyses and Robustness Checks

To reduce the possibility that our results are a result of our choice of empirical approach, we conducted several robustness checks. These address (a) model choice and specification, (b) measurement of variables, and (c) sample composition.

4.3.1. Model Choice and Specification. To ensure that our results are not specific to our choice of model specification, we used alternative specifications (Table 8).

First, we used a proportional hazard model to model when a claim resolves. Model A1 finds that basic EMRs ($\beta = 0.23$, $p < 0.01$) and advanced EMRs ($\beta = 0.51$, $p < 0.001$) are associated with faster claim resolution. Although confirmatory, we elected not to focus on this specification because claims in our analysis are not censored, and coefficients of ordinary least squares regression are easier to interpret.

Second, a mixed-level model mirrors the ordinary least squares model except that we allowed random intercepts for each hospital (Table 8, Model A2). Both basic ($\beta = -102.81$, $p < 0.001$) and advanced ($\beta = -218.62$, $p < 0.001$) EMRs are associated with a reduction in resolution time.

Table 7. Results of Claim Matching

	Before matching			After matching			
Variables	No EMRs	At least basic EMRs	Δ	No EMRs	At least basic EMRs	Δ	Improvement, %
Claim Load (ln)	0.308	−0.150	0.458	0.053	−0.027	0.080	82.5
Severity	0.158	−0.077	0.235	−0.015	0.004	−0.019	92.0
Employees (ln)	0.314	−0.153	0.467	−0.006	0.017	−0.023	95.1
Working Hours per Patient	0.337	−0.165	0.502	0.006	−0.094	0.100	80.1
Salary per FTE	−0.352	0.172	−0.524	−0.332	0.050	−0.382	27.1
Net Revenue per Patient	−0.613	0.299	−0.912	−0.453	0.181	−0.634	30.5
Geographic Index	0.295	−0.144	0.440	0.054	−0.094	0.147	66.5
Case Mix Index	0.142	−0.069	0.211	0.029	0.039	−0.010	95.4
Monetary Size	0.060	−0.029	0.089	−0.029	−0.013	−0.016	82.0
Claim Defendants (ln)	0.215	−0.105	0.320	−0.010	−0.032	0.021	93.3

Notes. Comparison of variables for claims against hospitals with no EMR functionality to those with at least basic EMR functionality before and after multivariate matching using a genetic search algorithm that determines the optimal weight for each variable. The No EMRs and At Least Basic EMRs columns represent the means for each variable, and Δ represents the difference of these means. The Improvement measure indicates the reduction in mean difference from the matching process (Iacus et al. 2012). All variables standardized.

Table 8. EMRs and Malpractice Claim Resolution Time: Alternative Models

	Hazard	Mixed	Truncated	Negative binomial	Time trends
Variables	Model A1	Model A2	Model A3	Model A4	Model A5
Hospital fixed effects	Yes	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes	
Hospital time trends (linear, quadratic)					Yes
Severity indicators	Yes	Yes	Yes	Yes	Yes
Constant		761.381	1,399.800	5.874***	2,441.057**
		(478.907)	(886.073)	(0.744)	(748.878)
Claim Load (ln)	−0.233***	115.533***	154.633***	0.114***	113.800***
	(0.005)	(2.481)	(3.554)	(0.003)	(2.777)
Employees (ln)	0.264*	4.503	−215.608**	−0.075	−260.270***
	(0.113)	(27.997)	(78.990)	(0.078)	(65.331)
Working Hours per Patient (std)	−0.037	−16.800	12.051	0.002	−15.823
	(0.041)	(14.357)	(24.299)	(0.017)	(29.478)
Salary per FTE (std)	0.613***	−315.633***	−406.100***	−0.312***	−454.202***
	(0.036)	(17.175)	(24.803)	(0.026)	(26.192)
Net Revenue per Patient (std)	0.309***	−102.617***	−142.204***	−0.122***	−158.336***
	(0.036)	(15.315)	(23.794)	(0.022)	(26.345)
Occupancy (std)	−0.067	−11.026	59.005*	0.046*	−3.194
	(0.039)	(14.331)	(25.937)	(0.020)	(26.063)
Geographic Index	0.004	3.122	−2.372	0.003	−0.928
	(0.008)	(3.279)	(5.268)	(0.004)	(4.508)
Case Mix Index	−0.532	400.254***	315.474	0.096	94.419
	(0.264)	(89.687)	(170.143)	(0.124)	(148.866)
Claim Defendants (ln)	−0.105***	61.597***	51.206***	0.059***	90.245***
	(0.023)	(11.787)	(14.461)	(0.011)	(13.437)
Monetary Size (/1000 $)	−0.00002**	0.020***	0.021***	0.00001**	0.025**
	(0.00001)	(0.004)	(0.005)	(0.00000)	(0.008)
Basic EMR	0.228**	−102.810**	−117.079*	−0.111**	−139.637**
	(0.070)	(33.018)	(45.825)	(0.036)	(50.540)
Advanced EMR	0.511***	−218.622***	−251.797***	−0.256***	−256.280***
	(0.075)	(35.647)	(49.537)	(0.039)	(55.248)
Log-likelihood	−22,867.640	−57,262.610	−57,262.610	−56,545.830	
AIC		114,573.200	114,573.200	113,487.700	

Notes. 7,411 observations; proportional hazard model (A1); multilevel mixed-effects linear regression (A2); truncated linear regression (A3); negative binomial regression (A4); linear regression with hospital specific time trends (A5). Standard errors clustered by hospital; (std) indicates standardized variables. AIC is Akaike information criteria.
***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

Third, because claims cannot be resolved before they occur (i.e., the minimum of *Resolution Time* is zero), the assumption of normal distribution of error terms in ordinary least squares regression could be violated. To account for this, we estimated a truncated regression model (Table 8, Model A3). Again, both basic ($\beta = -117.08$, $p < 0.05$) and advanced ($\beta = -251.80$, $p < 0.001$) EMRs are associated with a reduction in resolution time. Also, because *Resolution Time* is an integer count of the number of days, we estimated a negative binomial regression model (Model A4). Again, results are consistent for both basic ($\beta = -0.11$, $p < 0.01$) and advanced ($\beta = -0.26$, $p < 0.001$) EMRs. Results from a Poisson model (unreported) are consistent.

Fourth, in our focal model, year fixed effects control for a general time trend that might influence resolution time. We extended this by instead including linear and quadratic time trends for each hospital (Model A5). Results are consistent for both basic ($\beta = -139.64$, $p < 0.01$) and advanced ($\beta = -256.28$, $p < 0.001$) EMRs. (Because the hospital-specific linear and quadratic time trends could lead to collinearity with time-varying hospital covariates, we also ran models that exclude all hospital covariates and found similar results.)

4.3.2. Measurement of Variables. We do not observe the exact date when hospitals implemented component systems that comprise EMRs; we only observe the year. Therefore, EMRs might not have been in use for injuries that occurred early in the implementation year. To eliminate potential bias resulting from uncertainty about the specific implementation date, we ignored any claims during the year of EMR implementation (Table 9, Model C1). Results remain consistent for both basic ($\beta = -147.87$, $p < 0.001$) and advanced ($\beta = -253.89$, $p < 0.001$) EMRs.

Our analysis includes the *Claim Load* control variable, which measures the number of malpractice claims open at the same time and within the same court system (i.e., county) as the focal claim. We also define this measure as the number of open claims against the same hospital as the focal claim. (Note that the court-level measure encompasses the hospital-level measure.) We reran the analysis after replacing the court-level measure with the hospital-level measure (Table 9, Model C2). Results remain consistent for both basic ($\beta = -94.31$, $p < 0.01$) and advanced ($\beta = -127.81$, $p < 0.001$) EMRs.

4.3.3. Sample Composition. Because our unit of analysis is the claim, our results may implicitly grant more weight to larger hospitals. This could influence our results if larger hospitals all had (or did not have) EMRs. Therefore, we restrict our analysis to exclude claims filed against the top 5% of hospitals by size. We consider two measures of size. Model C3 excludes the top 5% of hospitals by claim volume. Results remain consistent for both basic ($\beta = -209.117$, $p < 0.001$) and advanced ($\beta = -271.28$, $p < 0.001$) EMRs. Alternatively, if we restrict our

Table 9. EMRs and Malpractice Claim Resolution Time: Alternative Measurements and Sample Composition Checks

	Without EMR adoption year	Using hospital-level claim load variable	Without 5% of largest hospitals by claim volume	Without 5% of largest hospitals by employees
Variables	Model C1	Model C2	Model C3	Model C4
Hospital fixed effects	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Severity indicators	Yes	Yes	Yes	Yes
Constant	1,335.394	−4,701.613***	1,150.431	1,749.942*
	(686.843)	(620.894)	(711.876)	(689.762)
Claim Load (ln)	113.831***	1,826.244***	117.985***	114.229***
	(2.756)	(31.762)	(3.132)	(2.815)
Employees (ln)	−204.115***	−295.625***	−197.470***	−265.704***
	(59.460)	(70.082)	(59.042)	(60.171)
Working Hours per Patient (std)	12.977	51.419***	9.884	4.493
	(20.577)	(14.214)	(17.358)	(16.042)
Salary per FTE (std)	−357.326***	−95.998***	−364.529***	−394.906***
	(26.026)	(18.267)	(29.694)	(27.097)
Net Revenue per Patient (std)	−133.955***	−58.936***	−132.904***	−113.376***
	(21.829)	(15.526)	(25.591)	(21.596)
Occupancy (std)	48.619*	−92.533***	50.505*	62.527**
	(20.220)	(18.225)	(21.071)	(20.392)
Geographic Index	0.531	−0.397	5.109	3.147
	(4.034)	(2.987)	(4.458)	(4.032)
Case Mix Index	285.165*	340.053***	−13.494	67.198
	(127.692)	(96.007)	(156.220)	(146.426)
Claim Defendants (ln)	59.693***	89.648***	65.296***	53.389***
	(14.012)	(9.771)	(15.370)	(14.107)
Monetary Size (/1000 $)	0.020**	0.016**	0.033**	0.024**
	(0.007)	(0.006)	(0.012)	(0.008)
Basic EMR	−147.873***	−94.312**	−209.109***	−165.870***
	(44.067)	(32.976)	(44.021)	(43.979)
Advanced EMR	−253.891***	−127.806***	−271.283***	−262.973***
	(45.836)	(34.319)	(45.549)	(45.526)
Observations	7,244	7,411	5,721	7,040
R^2	0.609	0.779	0.523	0.615
F	56.062***	129.038***	32.413***	55.724***

Notes. Ordinary least squares regression on claim resolution time that excludes the year of EMR implementation (C1), with *Claim Load* measured at the hospital level (C2), without 5% of the largest hospitals by claim volume (C3), and without 5% of the largest hospitals by employees (C4). Standard errors clustered by hospital; (std) indicates standardized variables.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

analysis to exclude claims filed against the top 5% of hospitals by number of employees (Model C4), again, results remain consistent for both basic ($\beta = -165.87$, $p < 0.001$) and advanced ($\beta = -262.97$, $p < 0.001$) EMRs.

Based on these alternative analyses, we conclude that our focal findings are robust to (a) model choice, (b) measurement choice, and (c) sample composition. We believe that the focal model (ordinary least squares regressions for 1999–2007 with claim covariates, hospital covariates, a flexible time trend, and hospital fixed effects) presents the most parsimonious and complete analysis of claim resolution time.

4.4. Investigating the Mechanism Behind the Effect

The evidence shows a negative relationship between EMRs and malpractice claim resolution time. We explore possible mechanisms for this relationship by examining heterogeneity, for example, whether EMRs have a stronger or weaker relationship for certain types of claims or hospitals or at different stages of the claim process.

First, we split our sample based on claim *Resolution Stage*. During the study period in Florida, malpractice claimants had to notify the hospital of their intent to initiate a malpractice claim. During this notification period, the claimant could request that the hospital provide medical records; this constitutes "informal" discovery (as opposed to "formal" discovery, which occurs after the claimant files a formal lawsuit).[3] After the notification period, the claimant may file a lawsuit if the claim remains unresolved. The lawsuit may or may not proceed to trial. The Florida system classifies

Table 10. EMRs and Malpractice Claim Resolution: Subsamples (Resolution Stage)

	Abandoned	Presuit	Pretrial	Trial
Variables	Model R1	Model R2	Model R3	Model R4
Hospital fixed effects	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Severity indicators	Yes	Yes	Yes	Yes
Constant	2,518.623	1,095.847	2,392.556	−10,207.940
	(1,530.087)	(924.786)	(1,231.241)	(12,346.100)
Claim Load (ln)	99.045***	48.615***	116.788***	20.130
	(9.464)	(8.140)	(10.524)	(117.309)
Employees (ln)	−279.125*	−91.124	−339.515*	−678.215
	(129.766)	(74.383)	(135.063)	(1,667.601)
Working Hours per Patient (std)	−20.955	18.352	26.006	−546.577
	(27.219)	(29.647)	(40.193)	(769.977)
Salary per FTE (std)	−523.559***	−409.002***	−309.156***	−584.442
	(42.791)	(32.871)	(37.887)	(608.489)
Net Revenue per Patient (std)	−22.577	−128.183***	−127.154***	−408.663
	(35.925)	(23.695)	(36.013)	(755.531)
Occupancy (std)	99.087**	34.887	68.997	−239.924
	(38.101)	(26.110)	(35.369)	(345.910)
Geographic Index	−1.975	−1.931	2.300	111.499
	(7.966)	(5.546)	(6.554)	(109.281)
Case Mix Index	−1.959	−158.773	680.557**	2,805.496
	(213.099)	(168.682)	(211.673)	(2,362.209)
Claim Defendants (ln)	31.867	104.104***	86.855***	189.700
	(29.963)	(22.100)	(17.163)	(248.073)
Monetary Size (/1000 $)	0.224*	0.004	0.037***	−0.013
	(0.102)	(0.007)	(0.008)	(0.011)
Basic EMR	−185.280	−157.991**	−87.198	−166.541
	(117.600)	(59.952)	(56.323)	(649.792)
Advanced EMR	−331.898**	−255.174***	−196.565**	566.592
	(124.274)	(62.360)	(62.296)	(755.136)
Resolution Time (subsample mean)	865.062	629.855	1613.107	2013.717
Change with Basic EMR (%)	−21.4	−25.1	−5.4	−8.3
Change with Advanced EMR (%)	−38.4	−40.5	−12.2	28.1
Observations	1,509	2,107	3,657	138
R^2	0.634	0.437	0.479	0.872
F	15.659***	9.388***	17.224***	2.608***

Notes. Ordinary least squares regression on claim resolution time in subsamples. Standard errors clustered by hospital; (std) indicates standardized variables.

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$.

claim resolution in one of the 11 stages (Table 2). We collapse these 11 stages into four categories and split the sample based on them: (1) before the suit is filed, labeled "presuit" (settlement reached prior to presuit period, within the presuit period, after arbitration begins or prior to suit being filed); (2) suit is filed but before trial, labeled "pretrial" (within 90 days of suit being filed, after suit filed prior to/during the settlement conference); (3) during or after trial, labeled "trial" (during trial but before court verdict, after court verdict, after notice of appeal is filed, during appeal, after appeal); and (4) abandoned (claim or suit abandoned), which may occur at any point during the process. We reran our focal regression on each subsample. As shown in Table 10, EMRs are most strongly associated with faster resolution for abandoned claims and presuit claims. Basic and advanced EMRs are associated with (a) a ~ 21% and ~ 38% speed improvement (respectively) for abandoned claims (although the coefficient for basic EMRs in this analysis is not significant, $p = 0.116$) and (b) a ~ 25% and ~ 41% speed improvement for presuit claims. By contrast, EMRs are associated with only a 5%–12% reduction in resolution time for claims resolved after claimants file suit but before trial, and they are not significantly associated with resolution time for claims resolved during or after trial.

These results suggest that EMRs—particularly advanced EMRs—help claims that resolve relatively quickly (including before claimants file suit) resolve even more quickly. One explanation for these results is that EMRs help the parties quickly gather and interpret data relevant to the claim, such as the nature and sequence of care administered. For abandoned claims, the clarity these data generate may convince claimants (or their attorneys) that their claims are unlikely to be successful, causing them to abandon them more quickly than they otherwise would have. For claims resolved before claimants file suit, this clarity may convince hospitals (or their insurers) that they were negligent (or at least that the costs of defending the claim outweigh the settlement amount) and should seek a resolution early in the process. Indeed, 91.6% of these claims resulted in an indemnity payment from the hospital's insurance company, which we consider a proxy for a payment made to the claimant. This rate is a significantly higher rate of payment ($p < 0.01$) than that for claims resolved before the trial begins (87.6%) or during or after trial (56.3%). The speed benefits of EMRs may also exist in claims that reach the lawsuit or trial stages, but difficult-to-avoid delays inherent to the court system, such as when judges are available for trial or for other steps, such as pretrial hearings, may counterbalance this benefit.

In a related analysis, we split our sample based on whether the claim included an indemnity payment, which (as noted) proxies for whether the claimant received a payment. Table 12 shows that EMRs are associated with a larger reduction in resolution time for "unpaid" claims than for "paid" claims (19% versus 9% for basic EMRs and 30% versus 16% for advanced EMRs). However, 68.4% of unpaid claims are abandoned. If we drop abandoned claims, the coefficients for basic and advanced EMRs for unpaid claims become −188 and −181 (respectively), are insignificant ($p = 0.183$ and $p = 0.249$, respectively), and imply a ~ 12% reduction in resolution time for both. Thus, it appears that the difference in the resolution time reduction between unpaid versus paid claims is because most unpaid claims are those that were abandoned. This is consistent with our conjecture that EMRs speed resolution of abandoned—and, therefore, unpaid—claims by helping claimants (or their attorneys) assess relatively quickly that claims are unlikely to be successful.

Extending this reasoning, Table 11 shows the average number of malpractice claims per hospital per year for each level of EMR use. These averages descriptively suggest that EMR use may relate not only to resolution time, but also to the number of claims: basic EMRs are associated with an increase in the number of claims (from 4.85 to 5.85 claims per hospital per year) while advance EMRs are associated with a net decrease (4.19 claims per hospital per year). Table 11 also shows the percentage of claims resolved at each stage and whether claims were paid or unpaid for each level of EMR use. EMR use is associated with a 12–15 percentage point increase in abandoned claims with most of this increase coming from a decrease in pretrial claims (Figure 3). Relatedly, EMR use is also associated with a 12–13 percentage point increase in unpaid claims. Although this descriptive analysis does not control for other claim attributes and trends, it supports our conclusion that EMR use is associated with claims being abandoned and, therefore, unpaid.

We also split the sample using other variables, such as claim severity (after collapsing the *Severity* variable into emotional/minor/major/death and temporary/permanent categories), whether the claim had one or multiple defendants (derived from *Claim Defendants*), and hospital size and case mix (using a median split based on *Employees* and *Case Mix Index*). Table 12 shows the results for hospital size. We found no meaningful differences in effect sizes (in terms of percentage changes from the means) across these subsamples.

Overall, the evidence suggests that EMRs have a clarifying effect that speeds claim resolution and that this applies to multiple hospital types and claim characteristics, such as severity. Based on the arguments presented in Section 2, including the general acceptance among the legal community that "the discovery

Table 11. EMRs and Malpractice Claim Resolution: Subsamples (Paid and Hospital Size)

	Indemnity paid?		Hospital size (by FTE)	
	No	Yes	Smaller	Larger
Variables	Model R5	Model R6	Model R7	Model R8
Hospital fixed effects	Yes	Yes	Yes	Yes
Year indicators	Yes	Yes	Yes	Yes
Severity indicators	Yes	Yes	Yes	Yes
Constant	1,810.976	2,103.305**	858.157	1,997.092*
	(1,272.894)	(740.495)	(940.240)	(990.923)
Claim Load (ln)	93.228***	123.566***	118.957***	107.881***
	(6.096)	(3.125)	(4.105)	(3.709)
Employees (ln)	−262.050*	−220.250**	−332.485**	−146.164
	(120.513)	(68.060)	(103.201)	(78.582)
Working Hours / Patient (std)	−26.002	9.076	21.850	−26.206
	(23.465)	(26.326)	(18.530)	(19.285)
Salary per FTE (std)	−455.350***	−328.198***	−372.263***	−357.839***
	(48.336)	(28.533)	(41.429)	(31.271)
Net Revenue / Patient (std)	−83.899*	−120.124***	−106.090**	−131.910***
	(36.849)	(24.731)	(37.192)	(24.317)
Occupancy (std)	69.920	54.387*	57.833	31.881
	(36.048)	(24.161)	(29.594)	(29.329)
Geographic Index	2.212	−3.309	6.519	−10.248
	(6.843)	(4.942)	(5.041)	(6.756)
Case Mix Index	328.035	310.839*	376.665	303.389
	(241.637)	(150.841)	(205.191)	(168.008)
Claim Defendants (ln)	40.992	55.866**	68.868***	51.542**
	(25.513)	(16.982)	(19.952)	(19.094)
Monetary Size (/1000 $)			0.033	0.017*
			(0.019)	(0.007)
Basic EMR	−206.950**	−107.397*	−124.577*	−153.976**
	(78.118)	(45.066)	(58.445)	(51.589)
Advanced EMR	−325.168***	−194.717***	−211.093***	−290.412***
	(81.688)	(48.349)	(60.973)	(55.838)
Resolution Time (subsample mean)	1068.623	1238.947	1081.275	1295.763
Change with Basic EMR (%)	−19.4	−8.7	−11.5	−11.9
Change with Advanced EMR (%)	−30.4	−15.7	−19.5	−22.4
Observations	2,186	5,225	3,699	3,712
R^2	0.610	0.630	0.521	0.656
F	17.642***	44.795***	25.063***	77.595***

Notes. Ordinary least squares regression on claim resolution time in subsamples. Standard errors clustered by hospital; (std) indicates standardized variables.
$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$.

phase is easily the most time consuming portion of most cases" (Stoel Rives 2012, HG.org 2016, FindLaw 2017), we believe that the reason EMRs are associated with faster resolution is that EMRs improve the efficiency (and speed) of discovery. This is particularly true for claims that do not reach the lawsuit stage or that are abandoned. EMRs may also speed the discovery process for claims that reach the lawsuit or trial stages, but delays inherent to the court system may countervail this effect.

A possible alternative explanation is that EMRs speed claim resolution by decreasing the number of claims filed against the hospital (or in the corresponding court system). This decreased workload—for both the hospital and the court system with jurisdiction over the claim—could cause claims to resolve faster. The *Claim Load* variable controls for this directly. In unreported analysis, we also disaggregated *Claim Load* and controlled for the number of claims by each *Severity* code. Controlling for these potential effects of claim load increases the likelihood that the coefficients of the *EMR* variables reflect resolution speed improvements because of more efficient discovery.

Table 12. EMRs and Malpractice Claim Volume

Group	No EMR (%)		Basic EMR (%)		Advanced EMR (%)	
Resolution stage						
Abandoned	0.38	(7.8)	1.35	(23.1)	0.82	(19.6)
Presuit	1.27	(26.2)	1.68	(28.7)	1.21	(28.9)
Pretrial	3.04	(62.7)	2.73	(46.7)	2.09	(49.9)
Trial	0.17	(3.5)	0.10	(1.7)	0.07	(1.7)
Indemnity paid?						
No	0.90	(18.6)	1.83	(31.2)	1.26	(30.1)
Yes	3.96	(81.6)	4.02	(68.7)	2.93	(69.9)
Total		4.85	5.85		4.19	

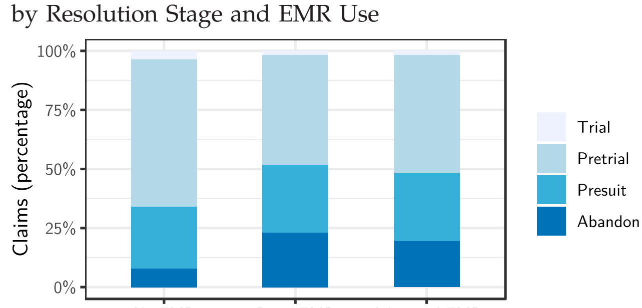
Note. Average number of claims per hospital per year.

5. Conclusion

Information systems increasingly generate, store, and analyze electronic trace data about what individuals do and when they do it. A growing body of research investigates the use of trace data for targeting advertising, determining trustworthiness and creditworthiness, and improving matching within markets. We focus on a relatively under-explored implication of trace data: how it influences the resolution of lawsuits. Specifically, we study how EMRs, which store trace data of what care was administered, when, and by whom, influence the resolution time of malpractice claims. Theoretically, EMRs could either speed or slow claim resolution, depending on whether the data they contain clarify or obfuscate the relevant issues. We collected a unique data set consisting of 7,411 resolved malpractice claims filed against 161 hospitals in Florida between 1999 and 2007. On average, each claim took more than three years to resolve. Our analysis finds that use of EMRs within a hospital at the time of the injury is associated with a more than four-month reduction in resolution time. We believe the reduction in resolution time is due to a streamlined discovery process made possible by the electronic paper trail generated by EMRs, including what care was administered (or not), when, and by whom. This is particularly true for claims that did not advance beyond the presuit period or that were abandoned. Faster resolution times are likely to generate economic savings, not to mention the emotional benefits they generate for providers and patients. Even if no payment is made to the patient, the cost of defending a malpractice claim is substantial. One study estimated the average cost to be $22,959 (standard deviation $41,687) (Seabury et al. 2012); another estimated it to be $88,090 (State of Connecticut Insurance Department 2019).

Our study makes three main contributions. First, it contributes to the understanding of how electronic trace data affects legal outcomes, specifically their resolution time. These effects are nonobvious a priori and warrant empirical examination because there are plausible arguments for why trace data might either speed or slow lawsuit resolution. The effect of electronic trace data on lawsuits is likely to be increasingly important in the future as society generates and stores more and more trace data. Second, our study has practical implications for the medical malpractice system. The lengthy time required to resolve malpractice claims creates substantial costs, both monetary and emotional, for providers and patients. There is a need to identify ways to make the system more efficient and timely. Whereas prior analysis has focused on the potential of tort reform to improve the system, healthcare information technology (specifically EMRs) can improve the system by speeding claim resolution time, leading to potentially substantial welfare benefits. Third, our study adds to a growing understanding of the costs and benefits of EMRs. EMRs offer many potential benefits, including better care and lower costs for individual patients as well as society (Devaraj and Kohli 2000, Koppel et al. 2005). Such benefits are at the root of the HITECH Act and the Meaningful Use standard (Blumenthal 2009). Our study offers empirical evidence of a previously unexamined benefit of EMR use: faster malpractice claim resolution. Given evidence that healthcare providers may be reluctant to install EMRs because of liability concerns (Miller and Tucker 2014), our research indicates a silver lining.

Figure 3. (Color online) Percentage of Malpractice Claims by Resolution Stage and EMR Use



Our study represents one of the first to investigate how trace data that information systems produce or store relates to legal outcomes. We focus on lawsuit resolution time, including investigating the mechanism by which trace data speed resolution, using EMRs and malpractice claims as our empirical context. In our context, the results suggest that trace data speeds resolution by clarifying the nature and sequence of care administered. Trace data appears to prompt claimants (or their attorneys) to abandon claims more quickly than they otherwise would have, perhaps because the clarity provided by the EMR data suggests that their claims would not be successful. It also appears that EMRs expedite the notification and informal discovery period that precedes the formal lawsuit, perhaps because the clarity provided by EMRs convinces the parties to seek a quick resolution. These findings may apply to other industries and areas of law. For example, trace data may lead to more legal matters being dropped or settled at relatively early stages, perhaps because the data quickly clarifies the merits (or lack thereof) of the matter. However, extrapolating to other contexts requires care because there are several factors related to how trace data might speed or slow lawsuit resolution, each of which might play a large role in a given context. Factors that might slow resolution include data redundancy and data security. For example, relevant data may be spread across multiple information systems. Checking for redundancy or otherwise integrating data across multiple systems creates an analytical burden that may create delay. Also, electronic storage and dissemination of evidence create data security and privacy considerations (Kim 2006). Handling these may add time to the process (Pace and Zakaras 2012). Factors that might speed resolution include search and communication efficiency. For example, IT tools, such as document review systems, facilitate searching through electronic data, often automating much of the process. For aspects of the analysis that cannot be automated effectively, electronic records can be distributed for parallel human processing if desired. Data can be stored, copied, and transferred more quickly and cost-effectively when electronic. This increase in communication efficiency has long been a benefit of information technology (Mendelson and Pillai 1998). Future research can seek to isolate how these and other factors affect lawsuit resolution time and other outcomes.

This study has important limitations. First, our data does not indicate how extensively each hospital used the component systems that comprise EMRs. Thus, our results reflect the relationship between an average degree of basic/advanced EMR use and claim resolution time. Second, because the research question necessitates studying a period in which claims have had time to resolve (we used the 1999–2007 period, having collected data through December 2019), we cannot be sure if our results hold for contemporary EMRs that may have more sophisticated functionality and for which use is deeper and more institutionalized. However, many of the key characteristics that make EMRs relevant to malpractice claim resolution, including the creation of metadata on system use (and nonuse) and the recording of electronic communication among caregivers, applied to EMRs during the 1999–2007 period as they do today. Third, because of the need to match data across multiple sources, we do not have a random sample of Florida hospitals. We assessed the representativeness of our sample using year 2000 data from the Florida Agency for Healthcare Information. Our sample includes 78% of the Florida hospital population and is representative on multiple measures, including percentage of teaching, public, and nonprofit hospitals, although the hospitals in our sample are slightly larger than average (317.8 beds versus 297.5 for the entire state). Fourth, our analysis is specific to Florida although the malpractice claim activity in Florida appears similar to many other states (Mello et al. 2003, Bishop et al. 2011, Jena et al. 2011). Fifth, although we employ multiple strategies to limit the possibility that unobserved attributes of claims and hospitals confound our results, we cannot rule out this possibility. For example, attributes such as the medical specialty associated with the claim may affect resolution time (Seabury et al. 2013) although we have no evidence that these attributes were distributed disproportionately across EMR-using and non-EMR-using hospitals in our study. Sixth, although our findings suggest that EMRs speed claim resolution via faster discovery, particularly during the early stages of the claim process, other mechanisms are possible. For example, EMRs could reduce claim resolution time by preventing errors that would otherwise lead to particularly long malpractice cases. Future research can further isolate the mechanism(s) through which EMRs speed claim resolution.

Endnotes

[1] For example, see https://www.healthit.gov/topic/health-it-basics/benefits-ehrs.

[2] The Florida Office of Insurance Regulation can be accessed at https://apps.fldfs.com/PLCR/Search/MPLClaim.aspx.

[3] For details, see the Florida Statutes, 1999–2007, sections 766.106 and 766.204, available at http://www.leg.state.fl.us/Statutes/.

References

Abelson R, Creswell J, Palmer GJ (2012) Medicare bills rise as records turn electronic. *New York Times* (September 21), https://www.nytimes.com/2012/09/22/business/medicare-billing-rises-at-hospitals-with-electronic-records.html.

Agarwal R, Gao G, DesRoches C, Jha AK (2010) The digital transformation of healthcare: Current status and the road ahead. *Inform. Systems Res.* 21(4):796–809.

Angst CM, Agarwal R (2009) Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *Management Inform. Systems Quart.* 33(2):339–370.

Angst CM, Agarwal R, Sambamurthy V, Kelley K (2010) Social contagion and information technology diffusion: The adoption of electronic medical records in U.S. hospitals. *Management Sci.* 56(8):1219–1241.

Angst CM, Devaraj S, Queenan C, Greenwood B (2011) Performance effects related to the sequence of integration of healthcare technologies. *Production Oper. Management* 20(3):319–333.

Autor DH (2003) Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *J. Labor Econom.* 21(1):1–42.

Balas EA (2001) Information systems can prevent errors and improve quality. *J. Amer. Medical Informatics Assoc.* 8(4):398–399.

Bertrand M, Duflo E, Mullainathan S (2004) How much should we trust differences-in-differences estimates? *Quart. J. Econom.* 119(1):249–275.

Bhargava HK, Mishra AN (2014) Electronic medical records and physician productivity: Evidence from panel data analysis. *Management Sci.* 60(10):2543–2562.

Bishop TF, Ryan AM, Casalino L (2011) Paid malpractice claims for adverse events in inpatient and outpatient settings. *JAMA* 305(23):2427–2431.

Bleier A, Eisenbeiss M (2015) Personalized online advertising effectiveness: The interplay of what, when, and where. *Marketing Sci.* 34(5):669–688.

Blumenthal D (2009) Stimulating the adoption of health information technology. *New England J. Medicine* 360(15):1477–1479.

Chan S (2008) When a MetroCard is an alibi. *New York Times* (November 19), https://cityroom.blogs.nytimes.com/2008/11/19/when-a-metrocard-is-an-alibi/.

Chodos JE (2015) Should there be specialty courts for medical malpractice litigation? *Columbia Medical Rev.* 1(1):10–22.

Cohendet P, Meyer-Krahmer F (2001) The theoretical and policy implications of knowledge codification. *Res. Policy* 30(9):1563–1591.

Curfman GD, Morrissey S, Drazen JM (2013) High-value healthcare—A sustainable proposition. *New England J. Medicine* 369:1163–1164.

Degnan D (2011) Accounting for the costs of electronic discovery. *Minnesota J. Law Sci. Tech.* 12(1):151–190.

Devaraj S, Kohli R (2000) Information technology payoff in the health-care industry: A longitudinal study. *J. Management Inform. Systems* 16(4):41–67.

Dexter PR, Perkins S, Overhage JM, Maharry K, Kohler RB, McDonald CJ (2001) A computerized reminder system to increase the use of preventive care for hospitalized patients. *New England J. Medicine* 345(13):965–970.

Diamond A, Sekhon J (2012) Genetic matching for estimating causal effects. *Rev. Econom. Statist.* 95:932–945.

Dimick C (2010) EHRs prove a difficult witness in court. Accessed July 20, 2020, http://bok.ahima.org/doc?oid=102634#.Xxci8S2z2wA.

Dranove D, Greenstein S, Goldfarb A, Forman C (2014) The trillion dollar conundrum: Complementarities and health information technology. *Amer. Econom. J. Econom. Policy* 6(4):239–270.

FindLaw (2017) Stages of a lawsuit. Accessed January 20, 2020, http://corporate.findlaw.com/litigation-disputes/stages-of-a-lawsuit.html.

Gallagher TH, Levinson W (2005) Disclosing harmful medical errors to patients: A time for professional action. *Arch. Internal Medicine* 165(16):1819–1824.

Gart M (2008) Medical malpractice: The first stage. *Physician Executive* 34(1):77–79.

Government Accountability Office (2003) Medical malpractice insurance: Multiple factors have contributed to increased premium rates. Report No. GAO-03-702. Government Affairs Office, Washington, DC.

Gray JE, Goldmann DA (2004) Medication errors in the neonatal intensive care unit: Special patients, unique issues. *Arch. Disease Childhood: Fetal Neonatal* 89(6):F472–F473.

Healthcare Information and Management Systems Society (2013) HIMSS Analytics Database. Accessed October 1, 2020, https://www.himssanalytics.org/.

Healthcare Information and Management Systems Society (2015) EMR adoption model. Accessed January 20, 2020, http://www.himssanalytics.org/emram.

Hersh W (2004) Healthcare information technology: Progress and barriers. *JAMA* 292(18):2273–2274.

HG.org (2016) Legal resources: Why does a lawsuit take so long? Accessed January 20, 2020, http://www.hg.org/article.asp?id=31734.

Hobgood C, Tamayo-Sarver JH, Elms A, Weiner B (2005) Parental preferences for error disclosure, reporting, and legal action after medical error in the care of their children. *Pediatrics* 116(6):1276–1286.

Hoffman S (2010) Employing E-health: The impact of electronic health records on the workplace. *Kansas J. Law Public Policy* 19:409–432.

Hoffman S, Podgurski A (2009) EHealth hazards: Provider liability and electronic health record systems. *Berkeley Tech. Law J.* 24(4):1523–1582.

Iacus SM, King G, Porro G (2012) Causal inference without balance checking: Coarsened exact matching. *Political Anal.* 20(1):1–24.

Institute of Medicine (2011) *Health IT and Patient Safety: Building Safer Systems for Better Care* (The National Academies Press, Washington, DC).

Jena AB, Seabury S, Lakdawalla D, Chandra A (2011) Malpractice risk according to physician specialty. *New England J. Medicine* 365(7):629–636.

Joos D, Chen Q, Jirjis J, Johnson KB (2006) An electronic medical record in primary care: Impact on satisfaction, work efficiency and clinic processes. *AMIA Annual Sympos. Proc.* (American Medical Informatics Association, Washington, DC), 394–398.

Kazley AS, Ozcan YA (2007) Organizational and environmental determinants of hospital EMR adoption: A national study. *J. Medical Systems* 31(5):375–384.

Kellermann AL, Jones SS (2013) What it will take to achieve the as-yet-unfulfilled promises of health information technology. *Health Affairs* 32(1):63–68.

Kessler DP (2011) Evaluating the medical malpractice system and options for reform. *J. Econom. Perspect.* 25(2):93–110.

Kim EKJ (2006) The new electronic discovery rules: A place for employee privacy? *Yale Law J.* 115(6):1481–1490.

Koppel R, Metlay JP, Cohen A, Abaluck B, Localio AR, Kimmel SE, Strom BL (2005) Role of computerized physician order entry systems in facilitating medication errors. *JAMA* 293(10):1197–1203.

Korin JB, Quattrone MS (2007) Electronic health records raise new risks of malpractice liability. Accessed October 1, 2020, https://www.law.com/legaltechnews/almID/1182194746807/.

Kuperman GJ, Bobb A, Payne TH, Avery AJ, Gandhi TK, Burns G, Classen DC, Bates DW (2007) Medication-related clinical decision support in computerized provider order entry systems: A review. *J. Amer. Medical Informatics Assoc.* 14(1):29–40.

Mangalmurti SS, Murtagh L, Mello MM (2010) Medical malpractice liability in the age of electronic health records. *New England J. Medicine* 363(21):2060–2067.

McNickle M (2011) 10 things you hate about your EMR. Accessed January 20, 2020, http://www.healthcareitnews.com/news/10-things-you-hate-about-your-emr.

Mearian L (2015) Lawyers smell blood in electronic medical records. *Computerworld* (April 13), https://www.computerworld.com/article/2909348/lawyers-smell-blood-in-electronic-medical-records.html.

Mello MM, Studdert DM, Brennan TA (2003) The new medical malpractice crisis. *New England J. Medicine* 348:2281–2284.

Mello MM, Chandra A, Gawande AA, Studdert DM (2010) National costs of the medical liability system. *Health Affairs* 29(9):1569–1577.

Mendelson H, Pillai RR (1998) Clockspeed and informational response: Evidence from the information technology industry. *Inform. Systems Res.* 9(4):415–433.

Menon NM, Kohli R (2013) Blunting Damocles' sword: A longitudinal model of healthcare IT impact on malpractice insurance premium and quality of patient care. *Inform. Systems Res.* 24(4):918–932.

Menon NM, Lee B, Eldenburg L (2000) Productivity of information systems in the healthcare industry. *Inform. Systems Res.* 11(1):83–92.

Miller AR, Tucker CE (2009) Privacy protection and technology diffusion: The case of electronic medical records. *Management Sci.* 55(7):1077–1093.

Miller AR, Tucker CE (2014) Electronic discovery and the adoption of information technology. *J. Law Econom. Organ.* 30(2):217–243.

Miller J, Glusko J (2003) Standing up to the scrutiny of medical malpractice. *Nursing Management* 34(10):20–22.

Miller RH, Sim I (2004) Physicians' use of electronic medical records: Barriers and solutions. *Health Affairs* 23(2):116–126.

Pace NM, Zakaras L (2012) Where the money goes: Understanding litigant expenditures for producing electronic discovery. Report, RAND Corporation, Santa Monica, CA.

Peckham C (2015) Medscape malpractice report 2015: Why most doctors get sued. Accessed January 20, 2020, http://www.medscape.com/features/slideshow/public/malpractice-report-2015.

Quinn MA, Kats AM, Kleinman K, Bates DW, Simon SR (2012) The relationship between electronic health records and malpractice claims. *Arch. Internal Medicine* 172(15):1187–1189.

Rehm S, Kraft S (2001) Electronic medical records: The FPM vendor survey. *Family Practice Management* 8(1):45–54.

Rosenbaum PR (2002) *Observational Studies* (Springer, New York).

Rosenbaum PR (2005) Sensitivity analysis in observational studies Everitt BS, Howell DC, eds. *Encyclopedia of Statistics in Behavioral Science*, vol. 4 (John Wiley & Sons, Hoboken, NJ), 1809–1814.

Rush JAW (2015) Health record audit trails: How useful is the metadata that is associated with a patient's health record? Accesssed July 20, 2020, https://www.nhdlaw.com/wp-content/uploads/2017/09/2015-Winter.pdf.

Sage WM (2004) Reputation, malpractice liability, and medical error. Sharpe VA, ed. *Accountability: Patient Safety and Policy Reform* (Georgetown University Press, Washington DC), 159–183.

Seabury S, Chandra A, Lakdawalla D, Jena AB (2012) Defense costs of medical malpractice claims. *New England J. Medicine.* 366(14): 1354–1356.

Seabury SA, Chandra A, Lakdawalla DN, Jena AB (2013) On average, physicians spend nearly 11 percent of their 40-year careers with an open, unresolved malpractice claim. *Health Affairs* 32(1):111–119.

Sen M (2014) How judicial qualification ratings may disadvantage minority and female candidates. *J. Law Courts* 2(1):33–65.

Sidorov J (2006) It ain't necessarily so: The electronic health record and the unlikely prospect of reducing healthcare costs. *Health Affairs* 25(4):1079–1085.

Simon SR, Kaushal R, Cleary PD, Jenter CA, Volk LA, Poon EG, Orav EJ, Lo HG, Williams DH, Bates DW (2007) Correlates of electronic health record adoption in office practices: A statewide survey. *J. Amer. Medical Informatics Assoc.* 14(1):110–117.

Soumerai S, Koppel R (2012) A major glitch for digitized health-care records. *Wall Street Journal* (September 17), https://www.wsj.com/articles/SB10000872396390443847404577627041964831020.

State of Connecticut Insurance Department (2019) Connecticut medical malpractice annual report. Accessed January 20, 2020, https://portal.ct.gov/-/media/CID/1_Reports/2019-CT-Medical-Malpractice-Report.pdf.

Stoel Rives (2012) How does a lawsuit work? Basic steps in the civil litigation process. Accessed January 20, 2020, https://www.stoel.com/legal-insights/article/how-does-a-lawsuit-work-basic-steps-in-the-civil-litigation-process.

Studdert DM, Mello MM, Brennan TA (2004) Medical malpractice. *New England J. Medicine* 350(3):283–292.

Studdert DM, Mello MM, Gawande AA, Gandhi TK, Kachalia A, Yoon C, Puopolo AL, Brennan TA (2006) Claims, errors, and compensation payments in medical malpractice litigation. *New England J. Medicine* 354(19):2024–2033.

Thorpe KE (2004) The medical malpractice "crisis": Recent trends and the impact of state tort reforms. *Health Affairs* 23:20–30.

Victoroff MS, Drury BM, Campagna EJ, Morrato EH (2012) Impact of electronic health records on malpractice claims in a sample of physician offices in Colorado: A retrospective cohort study. *J. General Internal Medicine* 28(5):637–644.

Vigoda MM, Lubarsky DA (2006) Failure to recognize loss of incoming data in an anesthesia record-keeping system may have increased medical liability. *Anesthesia Analgesia* 102(6): 1798–1802.

Virapongse A, Bates DW, Shi P, Jenter CA, Volk LA, Kleinman K, Sato L, Simo SR (2008) Electronic health records and malpractice claims in office practice. *Arch. Internal Medicine* 168(21): 2362–2367.

Wei Y, Yildirim P, Van den Bulte C, Dellarocas C (2015) Credit scoring with social network data. *Marketing Sci.* 35(2):234–258.