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The Effect of Electronic Medical Record Sophistication on U.S. Hospital Emergency Department Efficiency

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By

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ABSTRACT

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A key concern in emergency departments (EDs) is their overall efficiency, One proposed solution to making EDs more efficient is the use of electronic medical records (EMRs). This paper seeks to determine if varying levels of EMR sophistication have an effect on measures of emergency department efficiency.

Furukawa (2011) found that EMR sophistication had varying effects on ED efficiency. Fully functional EMRs significantly improved ED efficiency in multiple measures, while basic EMR varied on its effects on efficiency. Since Furukawa's results are somewhat inconclusive, this study aims to see if these effects are longstanding. I hypothesize that as EMR became more established, their effect on efficiency would become stronger. To this end, I used the 2009 National Hospital Ambulatory Care Survey (NHAMCS). I found that EMR sophistication does not have a strong association with ED efficiency. Five separate OLS regressions were used for five measures of ED efficiency. In order to account for possible endogeneity within the EMR related regressors, instrumental variables were used. In summary, based on the findings of this study and previous literature, it would seem that EMR sophistication does not conclusively affect ED efficiency.

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1. INTRODUCTION

Emergency departments (EDs) are integral in the US healthcare system today. The volume of ED patients has been increasing recently; the number of ED visits increased by 32% between 1999 and 2009. This increase in ED volume has led to substantial ED overcrowding and increased wait times (Hing and Bhuiya 2012). This is a major concern because emergency departments represent a vital part of the health care safety net in the US. The emergency department treats even those that do not have insurance and if overcrowding exists, these patients can not come to the ED to receive care. Overcrowding can reduce the safety of patients and can increase worries about public health if treatment takes longer than it should (Trzeciak and Rivers 2003). Patient flow and throughput can be affected by ED overcrowding, resulting in adverse patient health outcomes and patients going without care (Furukawa 2011). Although overcrowding may be the result of multiple and varied reasons, one proposed solution is the use of health information technology, specifically electronic medical records.

1.1 Background Information on Electronic Medical Records

Over the last twenty years, information technologies (IT) have dominated various industries, but only recently has it begun to have an impact on the healthcare industry (Hillestad et al.2005). Health care takes as many as 10-15 years to adopt information technologies when compared to other industries. The move towards a more technological medical setting began in the late 1960s and since then the US government has spent billions of dollars in order to automate certain health records systems. This has been evidenced in the various Electronic Health Record (EHR) systems arising such as the HealtheVet/VistA

system for Veteran Affairs (VA) hospitals and the Composite Health Care System (CHCS-II) for the Department of Defense. EHRs are said to be a building block of Health Information technology and they are talked about the most when it comes to health information technology. The problem with various EHR systems is that they can not transfer information between themselves (Goldschmidt 2005). Beginning in 1991, the Institute of Medicine has stated their strong belief that increased EHR would lead to improved health care quality (Romano and Strafford 2011). In 2004, President George W. Bush created the National Coordinator of Health Information Technology. The National Coordinator was tasked with making an EHR a reality for the majority of US residents within 10 years (Goldschmidt 2005). This goal may become easier to complete with the passing of the Health Information Technology for Economic and Clinical Health (HITECH) provisions of the American Recovery and Reinvestment Act of 2009 (Romano and Strafford 2011). HITECH has made the implementation of a nationally interoperable health information system a priority (Jha et al. 2009). Electronic Medical Records (EMR) refer to electronic records of patient medical data. Electronic Health Records (EHR) refer to a health information system that connects patients physicians and other medical personnel for the collective sharing of pertinent information. EMRs are required to be in place successfully before successful EHRs can be implemented (Garets and Davis 2006). This paper will focus solely on EMRs.

1.2 Potential Effects of EMR

EMRs are believed to have great potential effects on the quality of care, patient health, and costs of care. EMRs could reduce costs of care by eliminating costs of record keeping, improving workflow and efficiency, reducing medical error and repeat of tests, and

reducing the risk of malpractice lawsuits. EMRs could also improve the quality of health by reducing medical error and allowing for more transparency between different health care providers in an institution (Goldschmidt 2005).

The potential benefits of implementing an EMR system also depends on the level of sophistication the EMR has. EMR sophistication refers to the number of functionalities the EMR has. Certain EMR functionalities may have profound effects on quality of health such as clinical decision support systems (Romano and Strafford 2011). Other functionalities such as clinical documentation systems can increase the efficacy of charting patient information. Computerized physician order entry (CPOE) could possibly decrease the need to spend more time at the pharmacist. Very advanced EMRs may be able to coordinate care beyond the emergency room through an integrated hospital care system (Furukawa 2011).

1.3 Importance of Studying EMRs in the ED

Emergency departments represent key areas in hospitals where EMR might provide increased utility. In these areas of the hospital, the patients and physicians have limited prior interaction, if any at all. In addition to this, these centers tend to be highly trafficked and having an EMR may reduce costs and wasteful procedures in general. ED physicians do not know about the patients they are going to receive and thus accessing patient paper records in a timely manner is unlikely. Lastly, some patients that enter the ED may not be in a stable mental condition and thus would not be able to convey their precise medical condition accurately (Geisler et al. 2010). This contrasts with EMRs in a physician office setting, which are used also for the coordination of care, but also for the storing of ongoing patient

information (Bates et al. 2002). The degree to which a hospital uses an EMR system could have profound effects on the hospital's care and efficiency of their emergency departments.

1.3.1 Importance of Measuring Efficiency in the ED: Wait times

EMRs can help improve efficiency in the ED in multiple ways. One such way is to reduce ED wait times. ED overcrowding results in substantial wait times in the ED. Increased wait times have multiple consequences. Longer wait times can lead to dissatisfied patients (Hunt and Glucksman 1991). It has been shown that ED crowding has increased wait times as does the location of the hospital, urban hospitals having longer wait times than rural hospitals. The patient acuity level, how quickly the patient must be seen, also has a strong effect on wait time. Patients that need to be seen most quickly wait the least amount of time. In theory this seems fair, but patients that have minor conditions end up waiting longer than recommended for their condition because overcrowding exists (Hing and Bhuiya 2012). EMRs can possibly reduce these wait times by providing better regulated treatment and quicker laboratory and imaging results. Also certain EMR systems include discharge planning and automatic notification for beds, which in turn would improve ED wait times (Furukawa 2011).

1.3.2 Importance of Measuring Efficiency in the ED: Ambulance Diversion

Overcrowding additionally also results in ambulance diversions. Ambulance diversions occur when an emergency room is too crowded and can not accept any more patients so an incoming ambulance is diverted to another hospital. This can lead to delayed care for those in immediate need of it and can in some cases lead to transport-associated

deaths (Redelmeier et al. 1994). Handel and McConnell (2008) found that ambulance diversions actually lead to greater revenues for the hospital as the hospital electively chooses their patients. Thus no incentive exists from a monetary standpoint for a hospital to reduce their ambulance diversion times. Reducing ambulance diversion, though, can lead to increased quality of care and access to care. EMRs can reduce ambulance diversion times by reducing overcrowding in the ED. Thus EMRs have the potential to improve access to care and quality of health this way.

1.3.3 Importance of Measuring Efficiency in the ED: Test and Medication Orders

EMRs have the potential to improve the way tests and medications are ordered in the ED. Sophisticated EMRs are able to coordinate care effectively and allow for more timely administering of tests and medications. With medications and tests being administered more efficiently and in a more timely manner, patients can be seen more effectively, be given the care they require more efficiently, and be moved through the ED at a better pace and thus increase patient throughput (Marshall and Chin 1998).

1.3.4 Unintended Consequences of Implementing an EMR System

There can be adverse effects between EMRs and these measures of efficiency as well. It is possible that EMR implementation can lead to increased wait times instead of reducing them. Depending on the EMR, EMR use can lead to increased computer time and less time speaking with the patient directly, thus leading to dissatisfaction (Furukawa 2011). Also implementing an EMR can take some time, and during the initial period of implementation, wait times may increase as health care providers adjust to the new system (Baron et al. 2005).

EMRs can also affect the number of tests ordered in an undesirable way. As physicians gain access to more lab results through a computerized system, they might have more of an incentive to order tests since the results are so much more available to them. Thus EMR systems may not reduce the ordering of unnecessary tests, but may in fact increase the use of them (McCormick et al. 2012).

1.4 Focus of the Study

The following study aims to see if the sophistication of an EMR system based on the varying included functionalities increases ED efficiency as measured by wait times, ambulance diversion, readmission rates, and the number of tests ordered. Data was used from the National Health Ambulatory Care Survey (NHAMCS) for the years 2006 through 2009. NHAMCS is a survey conducted by the National Center for Health Statistics, a division of the Center for Disease Control and Prevention (CDC). I hypothesized that higher levels of EMR sophistication lead to higher levels of overall ED efficiency.

1.5 Contribution to Existing Literature

This paper will add to the existing literature since it uses more recent data than other papers on this topic. Research on the topic of EMR and its effects has been very inconclusive. Some research shows possible effects while others show complete lack of any effect. This paper adds to this research by showing that even up to a point more recently where EMRs are more implemented, there are still no conclusive results or improvements in efficiency as caused by the implementation of an EMR system.

1.6 Outline of the Paper

I will first describe the previous literature on this topic and how this paper will contribute to this existing body of work. Then will follow Section 2, a discussion of the methods used in this paper, including all the variables used and the regression techniques used for analysis. Section 4 will discuss the results of the study and Section 5 will end the paper with a discussion of the results and their implications, including a discussion of the limitations of the study.

2. LITERATURE REVIEW

EMRs have the potential to increase the efficiency of healthcare providers and improve health outcomes (Jha et al. 2009). Financial incentives were created for physicians and hospitals through Medicare and Medicaid for "meaningful use" of EMR systems as well (Geisler et al. 2010). Unfortunately, the research conducted up to now on the topic of EMR has not been entirely conclusive on what effects EMR can have. The literature on EMR falls into the following four categories: EMR’s Potential, EMR Implementation, Meaningful Use of EMR, and Effects of EMR Implementation.

2.1 EMR’s potential if implemented

EMRs are believed to have large potential benefits after their implementation. Wang et al. (2003) conducted a cost-benefit analysis of using an EMR for physician primary care practices. They found that up to possibly $86,400 per provider can be saved through the use of EMRs. This value can go higher depending on other sensitive factors as well. Most of these savings were found to come from reducing drug expenditures and decreased

radiological utilization. Hillestad et al. (2005) conducted a study analyzing the potential benefits and costs in implementing an EMR system. Their study involved estimating potential adoption costs, potential safety benefits, potential health benefits, and potential efficiency benefits. The study found that as much as almost $371 billion can be saved in the hospital setting through the implementation of EMRs. Many of the efficiency savings were also found to be due to reduced drug expenditures as well in this study. Both of these studies though are limited in that they may not have accounted for every applicable cost and benefit. Hillestad et al. (2005) had a strong limitation in that all of the costs and benefits are proposed and based on a scaling from a local or state level to the national level. Thus this study was limited by the fact that it only proposed potential benefits and costs of implementing an EMR system and did not find these benefits and costs empirically.

2.2 EMR Implementation

Multiple studies have been conducted to see how prevalent EMRs are throughout the US. These studies all show that EMR implementation is very low in the US. Jha et al. (2009) conducted their own survey to see how many hospitals that were part of the American Hospital Association (AHA) implemented EMRs. They used a categorical breakdown of EMR functionalities to see the implementation rates of the various categories across the US. They used three sets of EMR functionalities: basic, basic with clinical notes, and comprehensive. In the end they found that although many hospitals use various EMR functionalities on their own, only 1.5% of hospitals surveyed used comprehensive EMR, while 7.6% used basic EMR with clinical notes, and 10.9% used basic EMR without clinical notes.

The idea of designating different sets of EMR functionalities is not unique to Jha et al. (2009). Geissler et al. (2010) used the same sets of EMR functionalities as Jha et al. (2009) and applied it to hospital emergency departments for the years 2005 and 2006 to see the levels of implementation. Geissler et al. (2010) used the National Hospital Ambulatory Care Survey (NHAMCS) for the years 2005 and 2006. This survey asks questions to hospital emergency rooms about the presence of an EMR and various EMR functionalities. They studied the rate of implementation of any EMR and then considered the three categories listed above. Their findings were similar to Jha et al. (2009) in that less than 10% had comprehensive EMR systems and roughly 17% had a basic system. Furukawa 2011 used similar categories of EMR functionalities as well to ascertain EMR usage. He used the NHAMCS data for the year 2006 and found that only 10.8% had a basic EMR and only 1.7% had a fully functional EMR. It is clear based on these three studies that EMR implementation is low regardless of the definition. In my study, part of my analysis will involve seeing the usage of EMR systems over the time period between 2006 and 2009. I will most likely be using the same the breakdown of EMR functionalities as in Furukawa (2011.)

Many of the above studies on EMR implementation also found factors that influenced adoption of EMRs. Jha et al. (2009) found that being a large institution, being a major teaching center, being part of a larger hospital system, being located in an urban area, and having a dedicated coronary care unit were all hospital characteristics that positively influenced EMR adoption. Geissler et al. (2010) also found that being an urban region increased adoption of an EMR, and that the geographic region of the hospital affected EMR adoption, with the Northeast region having the highest EMR implementation. That last

finding is interesting because Furukawa (2011) found that the Midwest region had the largest influence on EMR adoption. In addition to this, he found that urban areas with higher median incomes and higher educational attainment led to higher levels of EMR adoption, while being government owned or for-profit tended to negatively affect EMR adoption. These factors are all hospital factors that may have an influence on EMR adoption. In my study I plan to use many of these same variables and in addition to them, include many patient and visit characteristics as well.

2.3 Meaningful use of EMR

The term "meaningful use" refers to Medicare and Medicaid reimbursement with respect to EMR use. Physicians and hospitals who employ EMR systems and are “meaningful users” of these systems will receive benefits from Medicare and Medicaid. It is not clear in the legislation and thus it is unclear for healthcare providers as to what level their EMR implementation must be to gain these rewards. Geisler et al. (2010) found that regardless of the definition of meaningful use used, US EDs were not implementing EMRs meaningfully. When they used “basic” as their definition of meaningful use, only 17% of US EDs were meaningful users of EMR, while if they chose to use a “comprehensive” definition, only 6% of US EDs qualified as meaningful users. Furukawa (2011) used categories of basic and fully-functional in his study. His findings show that a basic EMR is not sufficient to cause great changes in the ED, while a fully-functional EMR may be able to cause these changes. Thus it would seem that using EMRs that are highly sophisticated are good candidates for what legislation would call a “meaningful use” of EMR.

2.4 The Effects of EMR Implementation

2.4.1 Effects on Quality of Health

Research on how EMR implementation affects quality of health has shown mostly that EMRs have little or no effect on the quality of health. Linder et al. (2007) used the National Ambulatory Care Survey (NAMCS) for the years 2003 and 2004 to see if the presence of EMRs has an effect on 17 different quality indicators. The study found that the presence of EMRs throughout the two year span only had a positive effect on two indicators, no effect on fourteen indicators, and actually a negative effect on one indicator. Thus they concluded that there was no consistent effect on quality of health by EMR usage. Romano and Stafford (2011) conducted a follow up study to Linder et al. (2007) and wanted to see how EMR paired with clinical decision support (CDS) affected quality of health indicators. CDS should in theory be a functionality of EMR that directly and positively affects quality of health. They used the 2005-2007 NHAMCS data and compared the usage of EMR and CDS to any observed effects on 20 quality of health indicators. This study like Linder et al. 2007 found that EMR and CDS both had only a positively significant effect on one of the twenty indicators. Thus EMR usage even with CDS does not have an effect on quality. The two studies used indicators that involved whether physicians used correct treatments for varying conditions. Thus their measures of quality of health depended on correct treatment protocols. These two studies are pertinent to my study as they both use NAMCS/NHAMCS data and they consider EMR usage, but as they have shown that EMR usage does not have a significant effect on healthcare quality, the focus of my study shifted away from EMR's effect on quality of health.

2.4.2 Effects on Emergency Department Efficiency

Furukawa (2011) used stratified categories to see if these levels of EMR functionalities actually had an impact of emergency room efficiency. The measures of efficiency used were length of stay, wait time, treatment time, and occurrences of patients who left without treatment (LWOT). He found that hospitals with fully functional EMRs had strong negative effects on length of stay, wait time, and treatment time, while basic EMRs did not have significant relationships with the majority of variables, nor were any relationships linear. In essence, Furukawa showed that EMRs must be fully functional to have a "meaningful use" since basic EMRs did not have many significant effects. His finding has implications on policy as financial incentives should be focused on hospitals implementing fully functional EMRs in the future.

As shown by both Hillestad et al. (2005) and Furukawa (2011), EMR implementation can have significant impacts on hospital efficiency. Similar to Furukawa's study, I plan to analyze wait times, but I also plan to analyze readmission rates and the number of procedures and medications prescribed. All of these factors are indicators of hospital efficiency and can be strongly affected by EMR implementation. It is clear that not much research has been conducted on this topic yet and as such my study can contribute to the existing literature.

3. METHODS

3.1 Dataset

This study used the National Health Ambulatory Care Survey (NHAMCS) for the year 2009. This survey is conducted annually by the Center for Disease Control and Prevention (CDC). The survey collects data on services provided in hospital emergency and

outpatient departments in noninstitutional general and short-stay hospitals. The survey is separated into an emergency department component and an outpatient department component. The emergency department component is the focus of this study. The survey is a national (all fifty states and the District of Columbia) sample of hospitals and participation in the study for any hospital is completely optional. The survey is administered by specially trained interviewers which ensure that hospitals are eligible and know what they are doing. The survey is conducted through a form called the Patient Record Form, which is completed over a four week period in each hospital. Various information on patient and visit characteristics are included on this form. The survey also uses a hospital induction interview form to gather information on hospital characteristics, including EMR usage. Each observation in the survey defines one patient visit to the emergency department. In 2009, a total of 1,377 hospital emergency departments were surveyed and 140,415 emergency department patient visits were recorded. These numbers were weighted to represent a national sample of 18,970 hospital EDs and 495,826,926 ED patient visits. This estimation shows how widely used emergency departments are in this country and why an analysis on their efficiency is important.

3.2 Use of Sampling Weights in the Analysis

The NHAMCS is a survey that intends to represent characteristics of emergency departments and outpatient departments on a national scale. The original survey does not interview every single hospital in the nation and thus the data in the survey has to be scaled up to a national level. In order to make the data nationally representative, the survey makes use of sampling weights. Without the use of these weights, any analysis using the survey

data would produce biased results. The NHAMCS uses two specific sampling weights in the emergency department record: the patient visit weight for patient and visit characteristics, and the emergency department weight for hospital characteristics. These sampling weights help make the sample nationally representative, but more than just sampling weights is needed to use NHAMCS data accurately. When the NHAMCS conducts their survey, there are levels to how they conduct the survey to hospitals. First, the NHAMCS divides multiple geographic regions into strata. Within each strata, more divisions occur and each of these regions are denoted primary sampling units (PSUs) or clusters. Within each cluster, hospitals are used as the next level of analysis. Then within each hospital, outpatient clinics or emergency service areas are chosen. The final level to the NHAMCS analyzes patient visits within each outpatient clinic or emergency service area. This entire sampling process is used to reduce standard errors and create nationally representative data. This study used both types of sampling weights, the patient visit weight and the emergency department weight. The variables used in this study required the use of both kinds of weights. The majority of the analysis was conducted at the patient level and thus patient visit weights were the main type of sampling weight used. This study accounted for variances across clusters and strata using the related strata and cluster variables present in the NHAMCS (Pitblado 2012 and 2009 NHAMCS micro-data file).

3.3 EMR Sophistication

The important variable in this study was the presence of an EMR system. The NHAMCS asks “Does your ED use electronic medical records (EMR) (not including billing records)?” The survey also asks about the presence of an additional thirteen EMR

functionalities. Nonresponse and responses to these survey questions resulting in “unknown” and “turned off” were coded as not having the EMR system or function.

The classification of EMR sophistication was based on the classification used by Furukawa (2011). The three categories were minimal/no EMR, basic EMR, and fully functional EMR. “Minimal/no EMR” referred to hospitals that either had no EMR system or had an EMR system with less than the minimum set of EMR functions (patient demographic information, laboratory results, computerized order for tests, imaging results, clinical notes, and computerized orders for prescriptions). “Basic EMR” referred to hospitals with EMRs with at least the minimal set of EMR functions. “Fully functional EMR” was assigned to hospital EDs with the minimum set of EMR functions plus an additional seven advanced functions. These advanced functionalities included highlighting out of range levels, sending test orders electronically, having medical history and follow up notes, returning electronic images, warnings off drug interactions and contraindications provided, reminders for guideline-based interventions and/or screening tests, and prescriptions sent electronically to pharmacy (Furukawa 2011). Implementation of EMRs and associated functionalities for the year 2009 is shown in Table 1.

3.4 EMR Implementation in 2009

As shown in Table 1, EMR implementation was varied. When looking at overall EDs, the percent implementation was 73.8%, which is much higher than the 46.2% implementation for all EDs that Furukawa (2011) determined in 2006. Thus between 2006 and 2009, EMR implementation increased to a large extent. The individual functionalities also followed this same trend over the time period. Thus as more EMRs were adopted, EMR

became more sophisticated as well over this time period. Larger percentages of EMRs had more functions per EMR, even the more advanced functions, which were less implemented in 2006 (Furukawa 2011). Thus EMRs have become more widespread and also more sophisticated more recently. This would hopefully cause greater improvements in efficiency similar to the effects Furukawa (2011) found.

3.5 ED Efficiency

I used five measures of ED efficiency. All of these measures related to ED overcrowding and patient throughput. These measures included wait times, number of procedures given, number of medications prescribed, number of diagnostic tests given, and hours on ambulance diversion. Wait times were measured in minutes from entering the ED until seeing the physician. The variables for number of procedures, number of medications, and number of diagnostic tests were all measured as given in the NHAMCS and then each were divided by a measure for length of visit in the ED (measured in minutes). Thus measures for these variables per unit time in the ED were determined. Lastly, ambulance diversion was measured in total number of hours the ED spent on ambulance diversion for the year. The NHAMCS uses an ordered variable for hours on ambulance diversion. To create a continuous variable from this, I took the midpoint value for each ordered value and replaced all ordered labels with said midpoint value. Any responses with missing information for any of the above variables was excluded from the analysis. Descriptive statistics for these five variables are present on the next page in Table 2.

Table 2 provides good insight into the overall measures I studied, but it does not indicate much in terms of comparison or with relation to EMR presence. Thus I calculated

similar descriptive statistics for the five main variables, but across the EMR classification I used in this study. These values are present below in Table 3. Table 3 shows that for wait times, as EMR sophistication increased, so did the mean wait time. For number of procedures, number of medications, and number of diagnostic tests, as EMR sophistication increased, these values decreased, which is promising. Lastly ambulance diversion showed fluctuations, but showed a large reduction for fully functional EMR.

Table 1: Table showing the implementation of EMR and the various possible functionalities it can have. Implementation is shown for all EDs as well as broken down across the three classification levels of EMR sophistication: Minimal/no EMR, Basic EMR, and Fully Functional EMR. Estimates for average EMR functions used as each level as well as estimates for the population analyzed are also present.

		EMR Sophistication		
	All EDs	**Minimal or No EMR**	**Basic EMR**	**Fully Functional EMR**
Emergency Department (ED) uses EMR system, %	73.8	62.8	32.2	5.1
Functions included in EMR system,%				
Minimus set of EMR functions				
Patient Demographic Information	96.7	83.1	100.0	100.0
Laboratory Results	88.7	69.8	100.0	100.0
Computerized orders for tests	86.0	67.4	100.0	100.0
Imaging results	84.2	67.4	100.0	100.0
Clinical notes	68.2	32.9	100.0	100.0
Computerized orders for prescriptions	63.9	28.6	100.0	100.0
Advanced EMR functions				
Out of range levels highlighted	86.5	63.8	97.4	100.0
Test orders sent electronically	80.1	63.1	91.9	100.0
Medical history and follow-up notes	59.7	24.6	91.4	100.0
Electronic images returned	77.8	60.6	96.9	100.0
Warnings of drug interactions and contraindications provided	49.3	17.6	74.6	100.0
Reminders for guideline-based interventions and/or screening tests	35.3	13.6	42.1	100.0
Prescriptions sent electronically to pharmacy	24.5	9.7	21.5	100.0
EMR functions used, #	8.02	6.02	11.16	13.0
N (EDs)	337	166	135	36
Population (EDs)	4680	2938	1505	237
N (ED visits)	34,942	17,195	13,733	4,014
Population (ED visits; million)	136.1	67.0	53.5	15.6

Table 2: Descriptive statistics table showing the number of observations, mean, and standard deviation for the main dependent variables of this study. Variables for wait times and hours on ambulance diversion are broken down by patient acuity. Estimates here are at the patient level for all variables except hours on ambulance diversion. Ambulance diversion was analyzed at the emergency department level. Appropriate sampling weights from the 2009 NHAMCS were used to provide nationally representative data.

2009	Number	Mean	Standard Deviation
Wait time to see a physician (in min)			
All patients	31038	58.1	78.7
Patient acuity level/triage			
Immediate/emergent	3879	47.8	74.2
Urgent/semiurgent	23231	61.2	79.9
Nonurgent	3928	48.3	70.5
Number of Procedures			
All patients	32384	.39	0.85
Number of Medications			
All patients	33474	0.84	1.52
Number of Diagnostic Tests			
All Patients	33009	1.58	3.45
Hours on Ambulance Diversion (in hours)			
All patients	241	139.2	254.8
Patient acuity level/triage			
Immediate/emergent	38	147.4	293.2
Urgent/semiurgent	168	145.8	254.0
Nonurgent	35	98.6	214.0

Table 3: Table of descriptive statistics including number of observations, mean and standard deviation of the five dependent variables, stratified by EMR classification. All estimates are at the patient level except hours on ambulance diversion. Ambulance diversion was analyzed at the emergency department level. Appropriate sampling weights from the 2009 NHAMCS were used

	Number	Mean	Standard Deviation
Wait times (in minutes)			
Minimal/No EMR	17176	53.8	74.1
Basic	13716	61.6	81.7
Fully Functional	4010	67.8	89.4
Number of Procedures			
Minimal/No EMR	16051	0.42	0.90
Basic	12655	0.36	0.81
Fully Functional	3678	0.33	0.72
Number of Medications			
Minimal/No EMR	16438	0.89	1.55
Basic	13134	0.81	1.38
Fully Functional	3902	0.67	2.03
Number of Diagnostic Tests			
Minimal/No EMR	16299	1.64	3.00
Basic	12932	1.53	3.97
Fully Functional	3778	1.44	3.74
Hours on Ambulance Diversion (in hours)			
Minimal/No EMR	122	137.7	258.0
Basic	98	152.0	265.8
Fully Functional	21	88.1	173.9

3.6 Patient and Visit Characteristics

I included measures for patient characteristics including age, sex, race, ethnicity, expected source of payment, and the patient's residence into the models used in this paper. I also controlled for multiple visit related characteristics. These included patient acuity level/triage and the presence or specific chronic conditions. Descriptive statistics for these variables are present below in Table 4.

Table 4: Table of descriptive statistics for controls related to the patient and the patient visit. All estimates are weighted using sampling weights from the 2009 NHAMCS to make the results nationally representative.

	Mean	**Standard Deviation**
Age	36.3	24.1
Male	0.45	0.5
Female	0.55	0.5
Patient Residence		
Private Residence	0.91	0.29
Nursing Home	0.02	0.14
Homeless	0.004	0.068
Other residence	0.01	0.1
Ethnicity/Race		
Hispanic/Latino	0.14	0.35
White	0.68	0.47
Black	0.23	0.42
Asian	0.02	0.14
Pacific Islander	0.007	0.081
American Indian	0.007	0.086
More than one race	0.006	0.08
Payment Method		
Private Insurance	0.39	0.49
Medicare	0.17	0.38
Medicaid	0.3	0.46
Worker's Compensation	0.01	0.11
Self-pay	0.18	0.38
No charge	0.01	0.12
Payment Method Unknown	0.04	0.19
Patient Acuity		
Immediate/Emergent	0.12	0.32
Urgent/Semi-urgent	0.77	0.42
Nonurgent	0.11	0.31
Chronic Condition		
Cerebrovascular Disease	0.02	0.16
Congestive Heart Failure	0.03	0.17
Condition Requiring Dialysis	0.008	0.091
HIV	0.006	0.074
Diabetes	0.08	0.27
No Chronic Condition	0.8	0.4

Table 5: Table of descriptive statistics for controls related to the hospital ED and the area the hospital is located in. All estimates are weighted using sampling weights from the 2009 NHAMCS to make the results nationally representative.

	Mean	**Standard Deviation**
Teaching Hospital Status	0.1	0.3
MSA	0.82	0.39
Region		
Northeast	0.18	0.39
Midwest	0.25	0.43
South	0.39	0.49
West	0.18	0.38
Hospital Ownership		
Voluntary/non-profit	0.76	0.43
Government/non-federal	0.14	0.34
Proprietary Ownership	0.11	0.31
Percent Poverty		
Less than 5.00 percent	0.13	0.34
5.00-9.99 percent	0.24	0.43
10.00-19.99 percent	0.35	0.48
20..00 percent or more	0.22	0.42
Median Household Income		
$32,793 or less	0.3	0.46
$32,794-$40,626	0.25	0.43
$40,627-$52,387	0.21	0.41
$52,388 or more	0.18	0.38
Percent with Bachelor's Degree		
Less than 12.84 percent	0.33	0.46
12.84-19.66 percent	0.24	0.43
19.67-31.68 percent	0.21	0.4
31.69 percent or more	0.17	0.38
Urban-Rural Classification		
Large central metro	0.29	0.45
Large fringe metro	0.19	0.39
Medium metro	0.23	0.42
Small metro	0.07	0.26
Non-metro (micropolitan and non-core)	0.19	0.39

As can be seen in Table 4, most patients are white, pay by private insurance, are approaching middle age, and do not have chronic conditions.

3.7 Hospital and Area Characteristics

Several hospital characteristics were used to control for EMR usage. These characteristics include hospital ownership, teaching status, hospital region. Teaching status was inferred based on whether patients were seen by a resident or an intern. Hospital region is a geographic classification of where the hospital is located. Hospital ownership was classified as voluntary, non-federal governmental, and proprietary.

There were also some area characteristics based on the patient's zip code of residence. These included the percent of poverty, median household income, the percent of adults with at least a college education, and the urban/rural classification of the patient's zip code. Descriptive statistics on hospital and area characteristics are present on the previous page in Table 5. Table 5 shows that most hospitals are located in a metropolitan area, and are voluntary/non-profit hospitals.

4. RESULTS

4.1 Regression Models and Analysis

I performed five survey weighted survey-weighted ordinary least squares (OLS) regressions, one for each of the five ED efficiency variables. The variables for wait times and hours on ambulance diversion were log transformed prior to regression analysis. There were instrumental variable (IV) regressions as well for each of these five OLS

regressions. Wait times and ambulance diversion were also broken down within the regression models based on patient acuity levels.

In addition to these models, I used an additional model where the EMR classifications for basic and full were combined into one variable. I performed OLS and IV regressions for all five ED efficiency variables within this additional model as well. I estimated multiple regressions, all of which are summarized in Table 6 below. Table 6 only contains IV estimations; OLS estimations are present in the Appendix along with patient, visit, hospital, and area characteristic effects.

4.2 Tests for Endogeneity and Reverse Causality

There was concern that the implementation of EMR is endogenous. In particular, it is possible that more efficient hospitals would be quicker to implement more sophisticated EMR systems. Although various hospital characteristics are controlled for in this study, omitted hospital characteristics may be correlated with both EMR sophistication and ED efficiency, which would bias the results. Another possibility where endogeneity could arise is that less efficiency hospitals may adopt EMRs more readily to hopefully improve their efficiency. Instrumental variables (IV) were used to account for possible endogeneity. For IVs two dummy variables were used that are also part of the NHAMCS: one that indicated if EMRs had public health reporting and another that indicated if EMRs could send notifiable diseases electronically. These IVs were chosen because public health agencies have varied IT usage and sophistication, variation that existed across states. Since a possible source of endogeneity are EMRs that are implemented in response to efficiency needs or sustenance. EMRs that would have

public health reporting and notifiable disease reporting would most likely have these two functionalities as a response to public health needs or possible state or local government programs to improve public health. Thus these functionalities would exist in EMRs that were implemented not for any efficiency related reasons. Although information on public health and disease notification may have some effects on administrative processes in the ED setting, it was believed that these IVs were only correlated with EMR sophistication and not with ED efficiency and the clinical care processes involved within the ED (Furukawa 2011).

4.2.1 Results of Endogeneity and Reverse Causality Tests

Three tests were conducted to test the validity and use of the instrument variables. These tests produced varying results depending on the ultimate dependent variable used and the model used. The three tests used were an underidentification test, an overidentifying restrictions test, and endogeneity tests for the EMR regressors. When considering wait times, it appears that the IVs are not relevant as the underidentification test was not rejected in the model where basic and full are separate variables. In the model where basic and full are combined, the IVs are relevant and the underidentification test was rejected. The endogeneity tests for the basic and full EMR variables showed that the basic variable is exogenous (P=.0568), while the full variable is endogenous (P=.0058). The combined model for EMR shows that the combined EMR variable is also exogenous. Lastly an overidentifying restrictions test was performed for the combined model and the null hypothesis was rejected (P=.0375), meaning that the instruments are not strong or valid.

These tests were also conducted for the other dependent variables from the study. For number of procedures, in the model with two EMR regressors, the IVs were again not relevant. Basic was found to be endogenous (P=.0178), but full was determined to be exogenous (P=.286). The combined model was found to have relevant IVs, although not completely exogenous IVs (Hansen test P<.05). Additionally, the combined EMR variable was found to be exogenous as well (P=.2449).

For number of medications, the separated EMR model showed again that the IVs were not related to the EMR variables. Basic was found to be exogenous (P=.616) and full was determined to also be exogenous (P=.3352). In the combined model, the IVs were relevant, but weakly identifying (P=.1248 for test of overidentifying restrictions). Lastly, the combined EMR variable was found to be exogenous as well (P=.3864).

When considering number of diagnostic tests, the separated EMR model shows underidentification in terms of relevance again. Basic was found to be endogenous in this case (P=.0014) and full was determined to be exogenous (P=.2710). Lastly the combined model showed that the instruments were relevant and valid. Also the combined EMR model was very endogenous (P=0.00).

Lastly, with respect to ambulance diversion, both basic and full were underidentified and thus not related strongly to the IVs used.

As can be seen there is variation with respect to endogeneity of the EMR regressors as well as how valid and strong the IVs are. Overall, though it would appear that the use of instrumental variables is necessary and was done as such to create consistency across all models and variables. Additionally the results do not differ

significantly if only the OLS model were used and thus instrumental variables were the better choice as they account for possible endogeneity.

4.3 The Effect of EMR sophistication on Wait Times

As shown in Table 6, the presence and sophistication of EMR does not have any significant effects on wait times. Both in the model where basic and full are analyzed separately as well as where they are combined, wait time is unaffected by EMR presence and sophistication. Although EMRs do not have an effect on wait times, many of the patient and visit characteristics included in the regression do have significant relationships with wait times (see Appendix). Patients who lived in a nursing home saw significantly less wait times than patients who lived in other residences. There was also some indication of gender bias with wait times analyzed since men have shorter wait times than women. Many of the racial groups also saw shorter wait times than patients with multiple races. Most of the variables for chronic conditions were significantly related to wait times, but not all the same way. Congestive heart failure, HIV, and diabetes all increase wait times for patients. This is possibly due to their chronic condition meaning they are not in need of immediate acute care, but just routine care mostly and thus the hospital may rationalize them to wait longer or possibly they themselves are more comfortable with the longer wait (Grumbach et al. 1993). The exception to this though are patients requiring dialysis. These patients see significantly shorter wait times. Dialysis may occur more often and require more immediate treatment than the other chronic conditions and thus these patients may wait less (Friedman et al. 2000).

Within the hospital and area characteristics, the most interesting finding was that voluntary as well as governmental/non-federal hospitals both lead to longer wait times. This is an interesting finding since the majority of hospitals in this country are non-profit hospitals, either voluntary or state or local governmental ones (Bays 1983). Thus the majority of hospitals in this country seem to lead to longer wait times, at least when compared to proprietary owned hospitals. Although hospitals are seemingly seeing increased wait times, EMRs do not seem to be the solution to this issue.

4.4 The Effect of EMR Sophistication on the Number of Procedures Over Time

Similar to wait times, EMR sophistication was shown to have no effect on the number of procedures given in an ED, as shown in Table 6. Thus EMRs do not improve efficiency in this area either. There were some interesting patient and visit characteristics that did correlate with the number of procedures given (see Appendix). Age correlated strongly and positively with the number of procedures given in a certain time, which is reasonable. Older patients tend to be less healthy and require more care. Since they require more care and get sick more often, they would logically require more procedures to be performed (Yang et al. 2003). Again, patients living in a nursing home correlated strongly with this measure in that nursing home patients received more procedures than other patients. Nursing home patients are usually elderly patients who require more care than other patients and thus would need more procedures (Yang et al. 2003). Other interesting relationships are that males receive more procedures than females. It is possible that either men get sick more often, or that they seek care more often than females do. Hispanic patients interestingly receive significantly less timely care than

patients of multiple races. This may be an issue of access to care (Ku and Matani 2001). Patients who chose to pay through their private insurance plans or by worker's compensation saw increased number of procedures. This may be due to the fact that these plans are not capitated on their reimbursement and healthcare providers may abuse the system (Hashimoto 1996). It is also possible that patients with these plans seek care more often since they feel they will be covered regardless: a form of moral hazard in a way. Interestingly, the chronic conditions were not significantly related to the number of procedures given. This is interesting since chronic patients tend to use more healthcare than other patients (Grumbach et al. 1993). It is possible that the procedures that the NHAMCS categorize as "procedures" are not the kinds of procedures these chronic conditions require regularly.

None of the hospital or area characteristics showed significant relationships with the number of procedures performed.

4.5 The Effect of EMR Sophistication on the Number of Medications Over Time

Table 6 once again shows that EMR sophistication does not have any effect on the number of medications prescribed. Although EMR sophistication and implementation do not affect the number of medications given, there are some controls that do. Age is shown here again to be significantly correlated. Older patients as aforementioned tend to be sicker and require more care and this may also lead to increased number of medications in a given time to provide this increased care (Yang et al. 2002). In some models, patients who did not have to pay saw increased medication orders. This may be a result of the patient or the physician abusing the insurance system, similar to a moral

hazard problem. Congestive heart failure (CHF) also showed higher number of medications in a given time. Out of the multiple chronic conditions included in the NHAMCS, CHF may require the most amount of medicine given in a timely manner.

With respect to the hospital and area characteristics, only urban-rural classification showed significance. Areas with a large fringe metro classification or a medium metro classification lead to more medications given. Thus hospitals in these areas have communities that may require more medicine than other areas. This could also be due to patients who have specific medical conditions in these areas that require more medication.

4.6 The Effect of EMR Sophistication on the Number of Diagnostic Tests Over Time

As shown in Table 6, the number of diagnostic tests does not change with EMR sophistication or even if EMR is merely present. There were some other key variables that showed significant relationships with diagnostic testing. Within the patient and visit characteristics, age was very significant. This relationship is most likely related to the reasoning for why older patients also receive more procedures mentioned above (Yang et al. 2002). Also when looking at the chronic conditions. Many of these conditions significantly increased the number of diagnostic tests. This is logical as chronic conditions require more diagnostic testing regularly such as blood tests and imaging (Grumbach et al. 1993). The chronic conditions that were found to be significant were cerebrovascular disease, congestive heart failure, and diabetes. HIV and dialysis patients did not show significant relationships. The significance of some of these chronic conditions also may indicate why age is highly significant in this model. Certain

payment methods were also significant such as worker's compensation and patients who did not have to pay. This is most likely related to a similar reasoning mentioned above

Table 6: Table summarizes results from multiple regressions using Instrumental Variable (IV) models for the five dependent variables analyzed. Wait times is stratified by patient acuity levels. All estimates are nationally representative. Sampling weights from the 2009 NHAMCS were used to determine these estimates. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1). OLS regressions were also conducted with these dependent variables. Additionally multiple patient, visit, hospital, and area characteristics were regressed on these variables within these IV models as well as OLS models. The regression results for these other variables as well as complete OLS regression results are present in the appendix.

	Basic EMR	Fully Functional EMR	Basic or Fully Functional EMR
Wait time			
All patients	0.294 (0.647)	-0.0764 (0.565)	0.0895 (0.501)
Patient Acuity/Triage			
Immediate/emergent	-0.708 (0.758)	0.261 (0.840)	-0.230 (0.556)
Urgent/semiurgent	0.419 (0.805)	-0.312 (0.594)	-0.0188 (0.500)
Nonurgent	0.991 (0.738)	1.823 (1.401)	0.717 (0.593)
Number of Procedures			
All patients	0.259 (0.409)	-0.0345 (0.223)	0.0899 (0.272)
Number of Medications			
All patients	0.0676 (0.488)	-0.306 (0.429)	-0.139 (0.414)
Number of Diagnostic Tests			
All patients	1.492 (1.073)	0.879 (0.950)	1.145 (0.750)
Hours on Ambulance Diversion			
All patients	-5.734 (5.228)	-4.658 (5.154)	-5.200 (3.144)

for why worker's compensation and private insurance increased the number of procedures (Hashimoto 1996). These payment methods do not restrict the amount of care used and both the patient and the physician may take advantage of this fact.

With respect to hospital and area characteristics, hospitals with government/non-federal ownership significantly reduce the amount of diagnostic tests given. This may be due to a more price rationing ideology at these hospitals. Thus these hospitals are more conservative with their expenditures. With respect to efficiency, these hospitals are seemingly less efficient since they aim to reduce the number of diagnostic tests within a given time.

4.7 The Effect of EMR Sophistication on Ambulance Diversion Hours

Table 6 shows that EMR sophistication and implementation does not affect the number of hours a hospital goes on ambulance diversion. Unfortunately it also seems that none of the patient, visit, hospital, or area characteristics correlate with ambulance diversion either. Ambulance diversion may not be something that is caused by anything other than chance.

5. CONCLUSION

5.1 Summary of Findings

Although EMR was being more widely implemented in 2009, the potential efficiency effects of EMR sophistication and implementation discussed earlier in this paper were not found. Overall the presence and sophistication of an EMR system does not improve emergency department efficiency. Thus the reasoning behind the

implementation of an EMR system in a hospital ED should not be based on efficiency goals.

Although EMRs are not related to efficiency variables, many patient and visit characteristics were. Some of these characteristics included gender, age, payment method, and chronic conditions. Certain hospital and area characteristics such as hospital ownership and urban-rural classification were also related to some of the efficiency variables, but less so than patient and visit characteristics.

Thus going forward, hospital emergency departments may want to focus on these patient and visit characteristics to improve efficiency as EMRs as they exist now are not leading to efficiency improvements.

5.2 Relationship to Existing Literature

This paper showed that EMR sophistication and presence does not improve hospital ED efficiency. This finding contrasts the findings of Furukawa (2011). He found that EMR sophistication can actually reduce length of stay and treatment time when using 2006 NHAMCS data. My study's results are somewhat opposing to his findings, but the reason for this may be due to a couple differences in the two studies. Firstly, the only variable in common between the two studies is wait times, and Furukawa did not find that EMR sophistication improved wait times either. In fact he found that basic EMR significantly increased wait times (Furukawa 2011). Additionally, I used 2009 data whereas his study focused on 2006 data. It is likely that EMRs were in an earlier stage of implementation in 2006 and I originally hypothesized that as EMR implementation and sophistication increased over time, by 2009 EMRs should have had

an even greater effect on ED efficiency. As can be seen this was not the case. The reasoning behind a lack of relationship between EMR sophistication and ED efficiency in 2009 may be related to a maximization effect. By 2009, EMRs were more implemented and it is possible that there was a maximum efficiency improvement that could be attained through the use and implementation of EMR systems. Between 2006 and 2009, possibly this maximum was reached and thus this paper was not able to find any significant relationships between EMRs and emergency department efficiency.

This paper thus shows more of an inconclusive nature around the possible relationship between EMR sophistication and hospital ED efficiency. In the future, hospitals may want to use EMRs for other purposes such as improving the cost effectiveness of their operations and reducing medical errors and in addition to finding other uses for EMRs, hospitals may also want to find other mechanisms for improving ED efficiency.

5.3 Limitations of the Study

There were a number of limitations to this study. Firstly, a major limitation to this study regards EMRs themselves. There are multiple EMRs made by various companies currently. The main issue with EMRs is their lack of interoperability. EMRs are extensive within the hospital or physician practice they are implemented within, but patient information in one EMR does not transfer to another EMR in another hospital or practice, unless that medical practice or hospital is part of the same health system. Thus the coordination of care and potential benefits of EMR only extend as far as the institution in which they exist. Thus an analysis on if EMRs can improve hospital ED

efficiency does not look at the potential effect of a system that transfers and communicates health information across hospitals. Possible solutions to this limitation are to analyze the Veterans Affairs system that uses an integrative EHR (Kizer and Dudley 2009), or to wait until the US begins to implement widespread EHRs and then conduct a similar study to the one conducted in this paper.

Another major limitation in this paper is related to endogeneity issues. This paper addressed the possible endogeneity that exists between EMR sophistication and ED efficiency using an instrumental variable analysis. After conducting multiple tests on the endogeneity of the EMR variables and the strength of the IVs, it became clear that the IVs used were not good instruments. Thus the major limitation here was the lack of good instruments and thus the lack of a good way to address possible endogeneity issues. Instruments are not necessarily easy to find for a study, but if it is possible to find better ones for this specific research context, then those instruments should be used for future studies.

Another limitation was the lack of panel data for this topic. The dataset used was the NHAMCS and the NHAMCS is an optional, anonymous survey conducted across the country every year. Panel data would allow more analyses in this study. Thus one could also look into the changes in ED efficiency over a time period as a result of changes in EMR sophistication over time. This kind of study may be more revealing than the observational one done here.

5.4 Future Research

Several future research studies could be done to improve on the work done in this study. One such study would be to focus on the Veteran's Affairs (VA) VistA EHR system as it is an integrative healthcare system and overcomes issues of interoperability. The VA hospital system implemented EMRs much earlier than other hospitals and thus their EMRs may have substantial effects on efficiency in their hospitals. Now the VA system uses VistA, an integrative EHR system that began to be implemented in 1997. It had improved quality of care and operational performance greatly since its implementation and now the VA healthcare system is the largest integrated health system in the country (Kizer and Dudley 2009). Analyzing this system and seeing if the VA EHR contributes to higher levels of efficiency in VA hospital EDs could be a potential future study that would add to the current literature on EMRs/EHRs and hospital ED efficiency. Additionally, one could look at hospitals that are similar to one another, but where some hospitals use integrative EMRs or EHRs, while others do not and see if there is a significant difference. One could also study how the difference between integrative EMRs or EHRs and traditional non-integrative EMRs affects other factors such as cost effectiveness and medical errors.

Another possible future study would be more of an experimental study. One could implement an EMR system that utilizes a context based viewing system. This would involve an EMR system where data and information is stored in such a way that the way it is viewed changes depending on what kind of healthcare personnel is viewing the information. Thus the information would appear differently depending on if pharmacists, physicians, or nurses would be the ones viewing the information. The

overall information is the same, but it changes so as to make the most sense to whoever is viewing the information (Reddy et al.2009). One could implement such a system and see if this context based system improves ED efficiency over traditional EMR systems.

Lastly, a future research study could be conducted in which EMRs are analyzed within the physician office setting. Since physician offices provide longer term care and develop relationships with their patients, EMRs would act more like a patient information storage system and could help improve overall efficiency in the physician practice. To conduct such a study, one could use similar variables as in this study, but instead of using the NHAMCS, use the National Ambulatory Care Survey (NAMCS), which looks at physician offices.

Electronic medical records seemingly do not aid in improving hospital emergency department efficiency. Thus they may not be the solution to the overcrowding problem occurring in hospital EDs today. EMRs, however, can possibly help in other ways such as reducing overall medical costs and preventing medical errors. Hospital administrations should look for other methods by which to curb the growing issue of overcrowding in their EDs. Although EMRs may not help with the issue, they nonetheless should be considered for other uses by the hospital.

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7. APPENDIX

Table 7: First stage regression results for the patient level variables. Three first stage regressions are shown below, one for each EMR regressors used in any of the models analyzed in this paper. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

F-Stat	2.28	0.87	4.15
VARIABLES	basic	full	basic_or_full
epubhthe	0.150*	0.0341	0.184**
	(0.0861)	(0.0458)	(0.0879)
enotdise	-0.172	0.113*	-0.0591
	(0.108)	(0.0613)	(0.102)
age	-0.000961*	0.000489*	-0.000472
	(0.000506)	(0.000270)	(0.000524)
privres	-0.127	-0.0842	-0.211***
	(0.0814)	(0.0522)	(0.0697)
nurshome	-0.0957	-0.0986*	-0.194**
	(0.0881)	(0.0542)	(0.0791)
homeless	-0.133	-0.125	-0.258**
	(0.108)	(0.0781)	(0.0995)
male	-0.00526	-0.00884*	-0.0141**
	(0.00711)	(0.00490)	(0.00709)
ethun	0.0200	-0.0229	-0.00295
	(0.0499)	(0.0255)	(0.0488)
white	0.0169	-0.0626	-0.0457
	(0.0818)	(0.0649)	(0.0721)
black	0.0298	-0.0607	-0.0309
	(0.0866)	(0.0668)	(0.0755)
asian	-0.0720	-0.0260	-0.0980
	(0.0861)	(0.0619)	(0.0871)
pacisland	0.120	-0.109	0.0115
	(0.146)	(0.0856)	(0.134)
amerind	-0.160	-0.0611	-0.221*
	(0.111)	(0.0884)	(0.126)
paypriv	-0.00304	-0.0367	-0.0397
	(0.0377)	(0.0237)	(0.0380)
paymcare	-0.00862	-0.0256	-0.0342
	(0.0278)	(0.0215)	(0.0270)
paymcaid	-0.0310	-0.0273	-0.0584
	(0.0407)	(0.0240)	(0.0392)
paywkcmp	-0.0327	-0.0120	-0.0448
	(0.0440)	(0.0314)	(0.0450)
payself	-0.0877*	-0.0246	-0.112**

	(0.0529)	(0.0366)	(0.0564)
paynochg	-0.0899	0.0630	-0.0269
	(0.101)	(0.0814)	(0.112)
payoth	0.0552	-0.0264	0.0288
	(0.0727)	(0.0317)	(0.0710)
immediate	-0.00883	0.0487**	0.0398
	(0.0632)	(0.0211)	(0.0687)
urgent	-0.0467	0.0318	-0.0149
	(0.0474)	(0.0192)	(0.0520)
cebvd	-0.0348	0.00921	-0.0256
	(0.0494)	(0.0474)	(0.0505)
chf	0.0580*	-0.0178	0.0402
	(0.0322)	(0.0172)	(0.0309)
eddial	0.0409	0.00969	0.0506
	(0.0439)	(0.0307)	(0.0455)
edhiv	-0.0458	0.0493	0.00358
	(0.0600)	(0.0407)	(0.0618)
diabetes	0.00968	-0.00182	0.00786
	(0.0185)	(0.0144)	(0.0205)
resint	0.0135	-0.00816	0.00529
	(0.0738)	(0.0426)	(0.0653)
msa	0.185**	0.0947**	0.280***
	(0.0754)	(0.0459)	(0.0830)
northeast	0.0872	-0.0205	0.0667
	(0.112)	(0.0877)	(0.129)
midwest	0.00121	-0.00985	-0.00864
	(0.0959)	(0.0912)	(0.118)
south	0.0514	-0.0537	-0.00228
	(0.0860)	(0.0836)	(0.101)
voluntary	0.0305	0.00162	0.0321
	(0.0940)	(0.0586)	(0.101)
govnonfed	-0.0288	0.0424	0.0136
	(0.127)	(0.0711)	(0.127)
pov2	-0.0186	-0.0442*	-0.0628
	(0.0327)	(0.0255)	(0.0396)
pov3	-0.0223	-0.0119	-0.0343
	(0.0488)	(0.0299)	(0.0537)
pov4	-0.0661	0.0218	-0.0443
	(0.0632)	(0.0463)	(0.0658)
income2	-0.0907**	0.0341	-0.0566
	(0.0411)	(0.0331)	(0.0450)
income3	-0.0250	0.0352	0.0103
	(0.0595)	(0.0489)	(0.0637)
income4	-0.106	0.0202	-0.0859
	(0.0740)	(0.0563)	(0.0743)
degree2	0.0714*	-0.0116	0.0597

	(0.0363)	(0.0187)	(0.0363)
degree3	0.0669	-0.0336	0.0333
	(0.0465)	(0.0302)	(0.0504)
degree4	0.00120	-0.0303	-0.0291
	(0.0569)	(0.0428)	(0.0590)
urbanrur1	0.0818	-0.0237	0.0581
	(0.0780)	(0.0640)	(0.0703)
urbanrur2	-0.0885	-0.00886	-0.0974
	(0.0853)	(0.0633)	(0.0808)
urbanrur3	-0.0397	0.0471	0.00740
	(0.0665)	(0.0564)	(0.0687)
urbanrur4	-0.0137	-0.117***	-0.131
	(0.0798)	(0.0440)	(0.0844)
Constant	0.386**	0.154	0.540***
	(0.186)	(0.162)	(0.181)
Observations	30,359	30,359	30,359
R-squared	0.078	0.093	0.123

Table 8: First stage regression results for the ED level variables. Three first stage regressions are shown below, one for each EMR regressors used in any of the models analyzed in this paper. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

VARIABLES	(1) basic	(2) full	(3) basic_or_full
epubhthe	0.185*	0.0216	0.207**
	(0.0941)	(0.0426)	(0.103)
enotdise	-0.163*	0.0973**	-0.0652
	(0.0914)	(0.0470)	(0.111)
age	-0.00458**	0.00114	-0.00345
	(0.00205)	(0.000806)	(0.00215)
privres	0.0855	-0.107	-0.0217
	(0.162)	(0.0867)	(0.173)
nurshome	-0.0559	-0.185*	-0.241
	(0.207)	(0.103)	(0.229)
homeless	-0.406	0.504**	0.0981
	(0.257)	(0.238)	(0.358)
male	0.223***	-0.0541*	0.169***
	(0.0611)	(0.0310)	(0.0582)
ethun	-0.120	-0.00187	-0.122
	(0.128)	(0.0361)	(0.127)

white	-0.0600	0.0167	-0.0433
	(0.147)	(0.0586)	(0.141)
black	-0.0664	-0.00697	-0.0734
	(0.161)	(0.0619)	(0.159)
asian	-0.139	0.0219	-0.117
	(0.276)	(0.0741)	(0.260)
pacisland	-0.750***	0.0349	-0.715***
	(0.208)	(0.115)	(0.237)
paypriv	-0.174*	-0.00861	-0.183*
	(0.0905)	(0.0432)	(0.103)
paymcare	0.0813	-0.0498	0.0315
	(0.125)	(0.0459)	(0.121)
paymcaid	-0.278***	0.0380	-0.240**
	(0.0950)	(0.0379)	(0.111)
paywkcmp	-0.275	-0.0535	-0.329
	(0.249)	(0.0539)	(0.251)
payself	-0.332***	0.0138	-0.318**
	(0.114)	(0.0498)	(0.139)
paynochg	0.0201	-0.0603	-0.0402
	(0.223)	(0.0573)	(0.229)
payoth	0.413**	-0.0291	0.384*
	(0.186)	(0.0495)	(0.197)
immediate	-0.0883	0.0497	-0.0387
	(0.131)	(0.0388)	(0.138)
urgent	-0.000367	0.0462	0.0458
	(0.0983)	(0.0367)	(0.104)
cebvd	-0.610***	0.0375	-0.573***
	(0.186)	(0.0857)	(0.196)
chf	0.0558	0.0505	0.106
	(0.102)	(0.0638)	(0.103)
eddial	-0.246	-0.156	-0.402
	(0.347)	(0.139)	(0.372)
edhiv	0.472*	-0.124	0.348
	(0.248)	(0.0818)	(0.257)
diabetes	0.214	-0.0287	0.186
	(0.136)	(0.0507)	(0.148)
resint	0.0358	0.0194	0.0551
	(0.125)	(0.0585)	(0.123)
msa	0.307**	0.0547*	0.362***
	(0.124)	(0.0281)	(0.120)
northeast	-0.0283	0.0359	0.00755
	(0.127)	(0.0546)	(0.130)
midwest	-0.0837	0.0268	-0.0568
	(0.121)	(0.0582)	(0.127)
south	-0.0969	0.00649	-0.0904
	(0.109)	(0.0505)	(0.113)

voluntary	0.00896	-0.0415	-0.0325
	(0.111)	(0.0464)	(0.110)
govnonfed	0.0271	-0.0644	-0.0373
	(0.140)	(0.0522)	(0.131)
pov2	0.249**	-0.0569	0.192
	(0.104)	(0.0646)	(0.127)
pov3	0.205*	-0.0261	0.179
	(0.119)	(0.0496)	(0.143)
pov4	0.201	0.0116	0.213
	(0.186)	(0.0645)	(0.190)
income2	-0.116	-0.0183	-0.135
	(0.0934)	(0.0593)	(0.0972)
income3	-0.102	0.0239	-0.0780
	(0.127)	(0.0806)	(0.131)
income4	-0.0199	-0.0363	-0.0563
	(0.183)	(0.0831)	(0.180)
degree2	0.0134	-0.00572	0.00772
	(0.0815)	(0.0385)	(0.0883)
degree3	0.0455	-0.0432	0.00228
	(0.118)	(0.0342)	(0.127)
degree4	-0.00307	-0.0525	-0.0555
	(0.137)	(0.0418)	(0.144)
urbanrur1	-0.0818	0.0114	-0.0704
	(0.148)	(0.0555)	(0.138)
urbanrur2	-0.201	0.0248	-0.176
	(0.127)	(0.0606)	(0.123)
urbanrur3	-0.124	0.0355	-0.0884
	(0.128)	(0.0580)	(0.137)
urbanrur4	-0.210	-0.0656	-0.276*
	(0.150)	(0.0485)	(0.152)
Constant	0.397	0.0856	0.482
	(0.331)	(0.137)	(0.377)
Observations	292	292	292
R-squared	0.297	0.149	0.294

Table 9: Regression results for the multiple models regressed onto wait times. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Wait Time	(1)	(2)	(3)	(4)
basic_or_full		0.0925		0.0895
		(0.0820)		(0.501)

basic	0.0632		0.294	
	(0.0878)		(0.647)	
full	0.200		-0.0764	
	(0.124)		(0.565)	
age	0.000800	0.000860	0.00108	0.000859
	(0.000879)	(0.000877)	(0.000914)	(0.000891)
privres	-0.0291	-0.0286	-0.00664	-0.0292
	(0.0561)	(0.0533)	(0.114)	(0.109)
nurshome	-0.373***	-0.376***	-0.366***	-0.377***
	(0.0802)	(0.0789)	(0.111)	(0.109)
homeless	0.0771	0.0769	0.0979	0.0763
	(0.139)	(0.139)	(0.171)	(0.166)
male	-0.0852***	-0.0856***	-0.0856***	-0.0856***
	(0.0168)	(0.0168)	(0.0170)	(0.0169)
ethun	-0.0372	-0.0376	-0.0381	-0.0377
	(0.0729)	(0.0720)	(0.0719)	(0.0724)
white	-0.288***	-0.287***	-0.281***	-0.287***
	(0.0849)	(0.0834)	(0.0849)	(0.0837)
black	-0.125	-0.127	-0.129	-0.127
	(0.104)	(0.103)	(0.108)	(0.106)
asian	-0.418***	-0.413***	-0.387***	-0.413***
	(0.126)	(0.125)	(0.135)	(0.128)
pacisland	-0.522**	-0.531**	-0.558**	-0.530**
	(0.217)	(0.218)	(0.238)	(0.218)
amerind	-0.0814	-0.0754	-0.0363	-0.0760
	(0.152)	(0.150)	(0.188)	(0.171)
paypriv	-0.0239	-0.0263	-0.0262	-0.0264
	(0.0455)	(0.0451)	(0.0531)	(0.0534)
paymcare	-0.0609	-0.0617	-0.0591	-0.0619
	(0.0411)	(0.0410)	(0.0492)	(0.0483)
paymcaid	0.0368	0.0368	0.0452	0.0366
	(0.0460)	(0.0456)	(0.0578)	(0.0532)
paywkcmp	-0.0313	-0.0297	-0.0212	-0.0298
	(0.0820)	(0.0812)	(0.0924)	(0.0870)
payself	0.0197	0.0206	0.0369	0.0202
	(0.0660)	(0.0651)	(0.108)	(0.0961)
paynochg	0.286	0.289	0.304	0.289
	(0.198)	(0.198)	(0.206)	(0.196)
payoth	0.0540	0.0516	0.0438	0.0516
	(0.0730)	(0.0721)	(0.0684)	(0.0719)
immediate	-0.122*	-0.119	-0.116	-0.118
	(0.0712)	(0.0721)	(0.0846)	(0.0805)
urgent	0.200***	0.204***	0.216***	0.204***
	(0.0523)	(0.0526)	(0.0575)	(0.0523)
cebvd	-0.0487	-0.0444	-0.0312	-0.0445
	(0.0928)	(0.0905)	(0.0892)	(0.0900)

chf	-0.285***	-0.288***	-0.304***	-0.288***
	(0.0827)	(0.0837)	(0.0989)	(0.0914)
eddial	-0.211**	-0.207**	-0.201**	-0.207**
	(0.0917)	(0.0922)	(0.0962)	(0.0919)
edhiv	0.206*	0.214**	0.236**	0.214**
	(0.109)	(0.108)	(0.109)	(0.107)
diabetes	0.0724**	0.0716**	0.0690*	0.0716**
	(0.0337)	(0.0339)	(0.0357)	(0.0335)
resint	0.244***	0.245***	0.247***	0.245***
	(0.0878)	(0.0863)	(0.0797)	(0.0861)
msa	0.338**	0.341***	0.318	0.342*
	(0.132)	(0.130)	(0.193)	(0.189)
northeast	-0.0394	-0.0402	-0.0598	-0.0398
	(0.113)	(0.114)	(0.150)	(0.144)
midwest	-0.167*	-0.161*	-0.150	-0.160*
	(0.0865)	(0.0893)	(0.108)	(0.0968)
south	-0.0104	-0.0123	-0.0224	-0.0122
	(0.102)	(0.106)	(0.115)	(0.110)
voluntary	0.272***	0.269***	0.259**	0.269***
	(0.101)	(0.1000)	(0.1000)	(0.100)
govnonfed	0.308*	0.314**	0.334**	0.314**
	(0.157)	(0.156)	(0.162)	(0.157)
pov2	-0.0397	-0.0413	-0.0385	-0.0415
	(0.0472)	(0.0468)	(0.0504)	(0.0526)
pov3	-0.0484	-0.0453	-0.0335	-0.0454
	(0.0679)	(0.0669)	(0.0610)	(0.0660)
pov4	0.0274	0.0364	0.0644	0.0363
	(0.0733)	(0.0735)	(0.0741)	(0.0707)
income2	-0.00690	-0.00112	0.0219	-0.00130
	(0.0529)	(0.0534)	(0.0764)	(0.0591)
income3	-0.0983	-0.0918	-0.0751	-0.0918
	(0.0741)	(0.0737)	(0.0806)	(0.0742)
income4	-0.139*	-0.132	-0.102	-0.132
	(0.0809)	(0.0807)	(0.108)	(0.0834)
degree2	0.0309	0.0291	0.0165	0.0293
	(0.0552)	(0.0554)	(0.0627)	(0.0585)
degree3	0.0206	0.0180	0.00622	0.0181
	(0.0622)	(0.0620)	(0.0615)	(0.0584)
degree4	-0.0730	-0.0736	-0.0729	-0.0736
	(0.0730)	(0.0735)	(0.0788)	(0.0766)
urbanrur1	0.119	0.117	0.0996	0.117
	(0.103)	(0.102)	(0.108)	(0.104)
urbanrur2	0.0810	0.0863	0.114	0.0860
	(0.110)	(0.111)	(0.135)	(0.127)
urbanrur3	0.00430	0.0138	0.0372	0.0138
	(0.0904)	(0.0917)	(0.0983)	(0.0906)

urbanrur4	0.179*	0.170*	0.162	0.170
	(0.0921)	(0.0902)	(0.0984)	(0.103)
Constant	3.111***	3.096***	2.994***	3.098***
	(0.230)	(0.226)	(0.410)	(0.355)
Observations	26,620	26,620	26,620	26,620
R-squared	0.074	0.073	0.057	0.073

Table 10: Regression results for the multiple models regressed onto number of procedures. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Number of Procedures	(1)	(2)	(3)	(4)
basic_or_full		-0.0294		0.0899
		(0.0278)		(0.272)
basic	-0.0206		0.259	
	(0.0313)		(0.409)	
full	-0.0625**		-0.0345	
	(0.0267)		(0.223)	
age	0.000848**	0.000827**	0.00113**	0.000912**
	(0.000361)	(0.000362)	(0.000516)	(0.000354)
privres	0.0626*	0.0620**	0.109	0.0847
	(0.0320)	(0.0312)	(0.0899)	(0.0703)
nurshome	0.151***	0.151***	0.184**	0.171**
	(0.0441)	(0.0437)	(0.0806)	(0.0706)
homeless	-0.0681	-0.0677	-0.0193	-0.0409
	(0.0725)	(0.0725)	(0.134)	(0.120)
male	0.0581***	0.0584***	0.0595***	0.0598***
	(0.0118)	(0.0118)	(0.0127)	(0.0127)
ethun	-0.0809***	-0.0809***	-0.0791***	-0.0798***
	(0.0261)	(0.0260)	(0.0301)	(0.0264)
white	0.00426	0.00396	0.0172	0.00982
	(0.0303)	(0.0305)	(0.0348)	(0.0305)
black	-0.0259	-0.0257	-0.0182	-0.0212
	(0.0354)	(0.0355)	(0.0405)	(0.0352)
asian	0.0579	0.0560	0.0960	0.0699
	(0.0457)	(0.0460)	(0.0697)	(0.0549)
pacisland	-0.0211	-0.0186	-0.0379	-0.0194
	(0.0645)	(0.0649)	(0.0865)	(0.0726)
amerind	-0.0259	-0.0279	0.0324	-0.00360
	(0.0751)	(0.0760)	(0.127)	(0.104)
paypriv	0.0574***	0.0582***	0.0628**	0.0638***
	(0.0211)	(0.0209)	(0.0257)	(0.0225)

paymcare	-0.0199	-0.0193	-0.0155	-0.0153
	(0.0236)	(0.0236)	(0.0280)	(0.0267)
paymcaid	-0.0258	-0.0257	-0.0113	-0.0175
	(0.0193)	(0.0193)	(0.0293)	(0.0237)
paywkcmp	0.320***	0.319***	0.331***	0.325***
	(0.0722)	(0.0721)	(0.0773)	(0.0750)
payself	0.0140	0.0137	0.0408	0.0270
	(0.0269)	(0.0271)	(0.0399)	(0.0298)
paynochg	-0.0723	-0.0748	-0.0458	-0.0687
	(0.0556)	(0.0559)	(0.0670)	(0.0567)
payoth	-0.0698	-0.0689	-0.0778	-0.0701
	(0.0490)	(0.0484)	(0.0643)	(0.0541)
immediate	0.0706	0.0691	0.0663	0.0623
	(0.0460)	(0.0457)	(0.0507)	(0.0449)
urgent	-0.0694*	-0.0708**	-0.0601	-0.0705*
	(0.0361)	(0.0358)	(0.0474)	(0.0381)
cebvd	-0.0236	-0.0246	-0.0148	-0.0230
	(0.0305)	(0.0303)	(0.0395)	(0.0325)
chf	0.152**	0.153**	0.135*	0.147*
	(0.0727)	(0.0732)	(0.0753)	(0.0748)
eddial	0.0195	0.0190	0.0122	0.0135
	(0.0543)	(0.0543)	(0.0570)	(0.0549)
edhiv	-0.0738	-0.0764	-0.0618	-0.0782
	(0.0510)	(0.0514)	(0.0483)	(0.0490)
diabetes	0.0146	0.0147	0.0116	0.0131
	(0.0256)	(0.0254)	(0.0284)	(0.0260)
resint	-8.55e-05	-0.000130	-0.00243	-0.00150
	(0.0435)	(0.0435)	(0.0510)	(0.0458)
msa	-0.144**	-0.145**	-0.202	-0.178
	(0.0700)	(0.0702)	(0.126)	(0.118)
northeast	-0.0778*	-0.0782*	-0.102	-0.0927
	(0.0404)	(0.0409)	(0.0678)	(0.0584)
midwest	-0.0210	-0.0227	-0.0260	-0.0305
	(0.0377)	(0.0387)	(0.0521)	(0.0499)
south	-0.0245	-0.0237	-0.0375	-0.0279
	(0.0460)	(0.0464)	(0.0569)	(0.0510)
voluntary	-0.0708	-0.0699	-0.0744	-0.0691
	(0.0510)	(0.0507)	(0.0619)	(0.0536)
govnonfed	-0.0387	-0.0400	-0.0278	-0.0384
	(0.0669)	(0.0669)	(0.0734)	(0.0669)
pov2	-0.0133	-0.0129	-0.00203	-0.00571
	(0.0247)	(0.0247)	(0.0348)	(0.0310)
pov3	0.0282	0.0273	0.0388	0.0303
	(0.0334)	(0.0333)	(0.0413)	(0.0353)
pov4	-0.0176	-0.0203	0.00490	-0.0171
	(0.0333)	(0.0331)	(0.0460)	(0.0341)

income2	0.000355	-0.00159	0.0244	0.00497
	(0.0196)	(0.0202)	(0.0339)	(0.0225)
income3	-0.0125	-0.0145	-0.00418	-0.0164
	(0.0239)	(0.0242)	(0.0247)	(0.0237)
income4	0.0225	0.0203	0.0550	0.0304
	(0.0349)	(0.0354)	(0.0546)	(0.0419)
degree2	-0.0409	-0.0403	-0.0577	-0.0473
	(0.0321)	(0.0322)	(0.0426)	(0.0390)
degree3	-0.0515	-0.0503	-0.0698	-0.0561
	(0.0341)	(0.0341)	(0.0459)	(0.0394)
degree4	-0.00665	-0.00602	-0.00796	-0.00473
	(0.0358)	(0.0360)	(0.0371)	(0.0362)
urbanrur1	0.0162	0.0165	-0.00199	0.00779
	(0.0475)	(0.0469)	(0.0567)	(0.0467)
urbanrur2	0.0493	0.0481	0.0812	0.0612
	(0.0419)	(0.0417)	(0.0762)	(0.0611)
urbanrur3	0.0382	0.0351	0.0557	0.0346
	(0.0431)	(0.0428)	(0.0569)	(0.0428)
urbanrur4	0.00237	0.00527	0.0131	0.0201
	(0.0349)	(0.0354)	(0.0607)	(0.0586)
Constant	0.526***	0.531***	0.372	0.465**
	(0.0980)	(0.0973)	(0.257)	(0.185)
Observations	28,308	28,308	28,308	28,308
R-squared	0.024	0.024	0.000	0.019

Table 11: Regression results for the multiple models regressed onto number of medications. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Number of Medications	(1)	(2)	(3)	(4)
basic_or_full		-0.0482		-0.139
		(0.0437)		(0.414)
basic	-0.0146		0.0676	
	(0.0483)		(0.488)	
full	-0.170**		-0.306	
	(0.0725)		(0.429)	
age	0.00187**	0.00178**	0.00202**	0.00173**
	(0.000777)	(0.000781)	(0.000813)	(0.000767)
privres	0.0625	0.0682	0.0617	0.0500
	(0.0806)	(0.0841)	(0.119)	(0.132)
nurshome	-0.0827	-0.0728	-0.0905	-0.0883
	(0.110)	(0.113)	(0.128)	(0.141)

homeless	-0.225	-0.213	-0.234	-0.233
	(0.155)	(0.158)	(0.178)	(0.189)
male	0.0315*	0.0321*	0.0309	0.0311
	(0.0190)	(0.0190)	(0.0198)	(0.0203)
ethun	-0.0675	-0.0651	-0.0705	-0.0658
	(0.0469)	(0.0471)	(0.0469)	(0.0476)
white	0.0136	0.0219	0.00405	0.0167
	(0.0717)	(0.0784)	(0.0702)	(0.0836)
black	-0.00353	0.00571	-0.0149	0.00173
	(0.0762)	(0.0814)	(0.0759)	(0.0845)
asian	0.0784	0.0781	0.0830	0.0673
	(0.0999)	(0.103)	(0.120)	(0.122)
pacisland	0.216	0.234	0.191	0.233
	(0.177)	(0.179)	(0.182)	(0.172)
amerind	-0.0660	-0.0628	-0.0626	-0.0827
	(0.174)	(0.180)	(0.207)	(0.210)
paypriv	0.0838**	0.0894**	0.0778*	0.0849*
	(0.0397)	(0.0408)	(0.0404)	(0.0433)
paymcare	-0.0260	-0.0222	-0.0299	-0.0259
	(0.0392)	(0.0400)	(0.0427)	(0.0450)
paymcaid	0.0223	0.0253	0.0207	0.0190
	(0.0445)	(0.0456)	(0.0495)	(0.0509)
paywkcmp	0.151	0.153	0.151	0.148
	(0.0926)	(0.0928)	(0.0951)	(0.0949)
payself	0.0636	0.0647	0.0661	0.0540
	(0.0460)	(0.0473)	(0.0675)	(0.0641)
paynochg	-0.167*	-0.175**	-0.153	-0.180**
	(0.0865)	(0.0888)	(0.0977)	(0.0908)
payoth	0.174*	0.181*	0.165*	0.181*
	(0.0973)	(0.100)	(0.0928)	(0.104)
immediate	0.308***	0.302***	0.314***	0.307***
	(0.0735)	(0.0739)	(0.0744)	(0.0733)
urgent	0.0568	0.0514	0.0645	0.0511
	(0.0519)	(0.0518)	(0.0563)	(0.0513)
cebvd	-0.120	-0.124*	-0.115	-0.125*
	(0.0759)	(0.0725)	(0.0822)	(0.0727)
chf	0.271***	0.275***	0.264**	0.279**
	(0.102)	(0.103)	(0.108)	(0.108)
eddial	-0.0265	-0.0272	-0.0274	-0.0221
	(0.0871)	(0.0872)	(0.0946)	(0.0927)
edhiv	0.0353	0.0260	0.0479	0.0269
	(0.0945)	(0.0979)	(0.0927)	(0.0978)
diabetes	0.0262	0.0269	0.0249	0.0278
	(0.0410)	(0.0406)	(0.0423)	(0.0414)
resint	0.0360	0.0359	0.0357	0.0368
	(0.0494)	(0.0508)	(0.0484)	(0.0524)

msa	-0.260***	-0.267***	-0.261	-0.241
	(0.0964)	(0.0986)	(0.183)	(0.193)
northeast	-0.133*	-0.132	-0.140	-0.122
	(0.0796)	(0.0824)	(0.0934)	(0.0944)
midwest	-0.0231	-0.0258	-0.0208	-0.0218
	(0.0793)	(0.0837)	(0.0811)	(0.0843)
south	-0.123	-0.117	-0.132	-0.115
	(0.0828)	(0.0861)	(0.0812)	(0.0829)
voluntary	-0.0834	-0.0819	-0.0858	-0.0812
	(0.0983)	(0.101)	(0.0959)	(0.101)
govnonfed	-0.0868	-0.0909	-0.0809	-0.0913
	(0.109)	(0.112)	(0.109)	(0.114)
pov2	0.0105	0.0143	0.00758	0.00842
	(0.0380)	(0.0394)	(0.0440)	(0.0465)
pov3	-0.0100	-0.0101	-0.00893	-0.0128
	(0.0408)	(0.0421)	(0.0389)	(0.0420)
pov4	-0.0358	-0.0420	-0.0260	-0.0452
	(0.0550)	(0.0561)	(0.0602)	(0.0599)
income2	0.0396	0.0332	0.0503	0.0283
	(0.0413)	(0.0409)	(0.0504)	(0.0464)
income3	-0.0210	-0.0265	-0.0140	-0.0249
	(0.0482)	(0.0481)	(0.0518)	(0.0485)
income4	-0.0524	-0.0577	-0.0418	-0.0658
	(0.0654)	(0.0656)	(0.0851)	(0.0765)
degree2	-0.00881	-0.00584	-0.0150	-0.000594
	(0.0397)	(0.0404)	(0.0548)	(0.0535)
degree3	-0.0483	-0.0431	-0.0573	-0.0388
	(0.0517)	(0.0517)	(0.0664)	(0.0586)
degree4	0.0439	0.0463	0.0411	0.0453
	(0.0634)	(0.0631)	(0.0650)	(0.0624)
urbanrur1	0.0199	0.0261	0.00903	0.0320
	(0.0614)	(0.0622)	(0.0679)	(0.0626)
urbanrur2	0.176***	0.175***	0.182**	0.165**
	(0.0597)	(0.0591)	(0.0808)	(0.0756)
urbanrur3	0.150**	0.143**	0.159**	0.143**
	(0.0692)	(0.0711)	(0.0742)	(0.0704)
urbanrur4	0.111	0.126	0.0940	0.114
	(0.0794)	(0.0809)	(0.0898)	(0.0890)
Constant	0.879***	0.872***	0.868***	0.924***
	(0.215)	(0.228)	(0.292)	(0.303)
Observations	29,255	29,255	29,255	29,255
R-squared	0.016	0.016	0.015	0.015

Table 12: Regression results for the multiple models regressed onto number of diagnostic tests. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

Number of Diagnostic Tests	OLS (1)	OLS (2)	IV (3)	IV (4)
basic_or_full		-0.0425		1.145
		(0.0902)		(0.750)
basic	-0.0138		1.492	
	(0.0999)		(1.073)	
full	-0.149		0.879	
	(0.117)		(0.950)	
age	0.0182***	0.0182***	0.0194***	0.0189***
	(0.00172)	(0.00170)	(0.00219)	(0.00187)
privres	0.0598	0.0579	0.330	0.280
	(0.135)	(0.133)	(0.243)	(0.201)
nurshome	0.303	0.306	0.521*	0.497**
	(0.193)	(0.191)	(0.275)	(0.251)
homeless	-0.378*	-0.377*	-0.0791	-0.123
	(0.223)	(0.222)	(0.331)	(0.293)
male	-0.0841**	-0.0835**	-0.0720*	-0.0713*
	(0.0395)	(0.0395)	(0.0405)	(0.0402)
ethun	-0.0829	-0.0825	-0.0761	-0.0754
	(0.0741)	(0.0744)	(0.105)	(0.0947)
white	-0.0665	-0.0672	-0.00718	-0.0192
	(0.116)	(0.116)	(0.150)	(0.136)
black	-0.230*	-0.229*	-0.195	-0.198
	(0.124)	(0.124)	(0.168)	(0.153)
asian	0.256	0.250	0.434*	0.383*
	(0.157)	(0.159)	(0.235)	(0.222)
pacisland	-0.0654	-0.0571	-0.107	-0.0675
	(0.258)	(0.256)	(0.427)	(0.373)
amerind	-0.277	-0.284	0.0255	-0.0460
	(0.350)	(0.352)	(0.424)	(0.394)
paypriv	0.112	0.115	0.168	0.169*
	(0.0912)	(0.0907)	(0.105)	(0.101)
paymcare	0.149	0.150	0.194*	0.193**
	(0.0952)	(0.0949)	(0.0997)	(0.0978)
paymcaid	-0.0260	-0.0256	0.0651	0.0524
	(0.0868)	(0.0865)	(0.116)	(0.107)
paywkcmp	-0.530***	-0.531***	-0.465***	-0.481***
	(0.150)	(0.151)	(0.164)	(0.161)
payself	-0.00640	-0.00734	0.156	0.127

	(0.0779)	(0.0785)	(0.154)	(0.131)
paynochg	-0.448***	-0.457***	-0.347	-0.398**
	(0.170)	(0.173)	(0.211)	(0.194)
payoth	-0.0791	-0.0766	-0.0979	-0.0849
	(0.149)	(0.147)	(0.201)	(0.184)
immediate	0.931***	0.927***	0.872***	0.864***
	(0.244)	(0.245)	(0.275)	(0.263)
urgent	-0.0232	-0.0279	-0.00330	-0.0252
	(0.190)	(0.191)	(0.219)	(0.204)
cebvd	0.458***	0.455***	0.487***	0.469***
	(0.150)	(0.148)	(0.173)	(0.163)
chf	0.756***	0.759***	0.677***	0.701***
	(0.119)	(0.119)	(0.131)	(0.117)
eddial	0.384*	0.383*	0.318	0.322
	(0.209)	(0.208)	(0.227)	(0.222)
edhiv	0.424*	0.416*	0.439*	0.403*
	(0.234)	(0.236)	(0.236)	(0.234)
diabetes	0.287***	0.287***	0.271***	0.275***
	(0.0790)	(0.0791)	(0.0787)	(0.0790)
resint	0.0317	0.0311	0.0125	0.0129
	(0.108)	(0.109)	(0.152)	(0.142)
msa	0.000209	-0.00207	-0.381	-0.331
	(0.150)	(0.151)	(0.283)	(0.248)
northeast	-0.0791	-0.0809	-0.231	-0.215
	(0.166)	(0.168)	(0.273)	(0.253)
midwest	0.246	0.240	0.191	0.178
	(0.181)	(0.183)	(0.266)	(0.255)
south	0.199	0.201	0.153	0.169
	(0.186)	(0.187)	(0.235)	(0.231)
voluntary	-0.249	-0.246	-0.257	-0.244
	(0.212)	(0.211)	(0.238)	(0.221)
govnonfed	-0.493**	-0.496**	-0.467*	-0.484**
	(0.227)	(0.228)	(0.249)	(0.238)
pov2	0.0724	0.0739	0.154	0.147
	(0.0690)	(0.0692)	(0.100)	(0.0943)
pov3	0.0891	0.0866	0.136	0.119
	(0.0952)	(0.0957)	(0.131)	(0.120)
pov4	-0.0611	-0.0700	0.00987	-0.0367
	(0.0847)	(0.0862)	(0.139)	(0.108)
income2	-0.0884	-0.0948	0.00737	-0.0329
	(0.106)	(0.108)	(0.151)	(0.124)
income3	-0.123	-0.130	-0.129	-0.154
	(0.117)	(0.117)	(0.130)	(0.122)
income4	-0.0261	-0.0338	0.121	0.0672
	(0.128)	(0.129)	(0.187)	(0.164)
degree2	-0.00341	-0.00130	-0.0934	-0.0711

	(0.0902)	(0.0912)	(0.113)	(0.106)
degree3	-0.0409	-0.0367	-0.125	-0.0955
	(0.0824)	(0.0837)	(0.0996)	(0.0934)
degree4	0.0977	0.0997	0.103	0.110
	(0.0978)	(0.0992)	(0.127)	(0.125)
urbanrur1	-0.217*	-0.216*	-0.317*	-0.298*
	(0.117)	(0.116)	(0.187)	(0.168)
urbanrur2	-0.0476	-0.0520	0.127	0.0828
	(0.105)	(0.104)	(0.200)	(0.165)
urbanrur3	-0.0963	-0.106	-0.0610	-0.106
	(0.107)	(0.105)	(0.160)	(0.126)
urbanrur4	0.209	0.218	0.355	0.368
	(0.152)	(0.154)	(0.268)	(0.249)
Constant	1.056**	1.072**	0.239	0.426
	(0.483)	(0.487)	(0.793)	(0.688)
Observations	28,868	28,868	28,868	28,868
R-squared	0.059	0.059	0.013	0.027

Table 13: Regression results for the multiple models regressed onto number of diagnostic tests. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

Ambulance Diversion	OLS (1)	OLS (2)	IV (3)	IV (4)
basic_or_full		-0.476**		-5.200
		(0.230)		(3.144)
basic	-0.463*		-5.734	
	(0.243)		(5.228)	
full	-0.564		-4.658	
	(0.403)		(5.154)	
age	0.00599	0.00570	0.0190	0.0208
	(0.00565)	(0.00586)	(0.0221)	(0.0168)
privres	1.200	1.249	-2.217	-2.435
	(0.919)	(0.893)	(4.072)	(3.288)
nurshome	-0.936	-0.882	-2.862	-3.242
	(1.134)	(1.088)	(4.426)	(3.174)
male	-0.444	-0.440	1.253	1.079
	(0.281)	(0.279)	(1.824)	(1.203)
ethun	-0.517	-0.518	-0.440	-0.435
	(0.476)	(0.477)	(1.047)	(0.989)
white	0.359	0.357	0.378	0.398

	(0.454)	(0.454)	(0.844)	(0.754)
black	0.545	0.536	0.0345	0.160
	(0.468)	(0.474)	(1.618)	(1.087)
pacisland	0.571	0.561	-3.051	-2.676
	(1.129)	(1.125)	(4.295)	(2.994)
paypriv	-0.489	-0.489	-3.049	-2.854
	(0.378)	(0.379)	(2.649)	(1.918)
paymcare	0.0244	0.0326	-2.073	-1.991
	(0.489)	(0.496)	(1.823)	(1.497)
paymcaid	-0.282	-0.292	-2.832	-2.538
	(0.352)	(0.345)	(2.947)	(1.823)
payself	-0.435	-0.440	-4.434	-4.079
	(0.454)	(0.454)	(4.109)	(2.790)
paynochg	0.0760	0.0856	-5.885	-5.521
	(0.773)	(0.782)	(5.469)	(3.966)
immediate	0.969**	0.952*	4.023	3.955*
	(0.474)	(0.479)	(2.524)	(2.284)
urgent	0.0108	-0.00208	3.320	3.191
	(0.344)	(0.347)	(2.691)	(2.381)
cebvd	-0.490	-0.474	-1.346	-1.434
	(0.599)	(0.586)	(2.018)	(1.807)
chf	-1.012	-1.003	-1.507	-1.563
	(0.642)	(0.642)	(1.594)	(1.451)
diabetes	1.030**	1.034**	-0.619	-0.527
	(0.439)	(0.443)	(2.174)	(1.838)
resint	1.385***	1.383***	-0.422	-0.267
	(0.448)	(0.456)	(2.244)	(1.932)
msa	-1.111	-1.129	1.176	1.171
	(0.773)	(0.785)	(1.987)	(1.825)
northeast	-0.388	-0.394	1.141	1.085
	(0.374)	(0.375)	(1.577)	(1.342)
midwest	-1.053***	-1.058***	-0.884	-0.852
	(0.348)	(0.345)	(0.936)	(0.803)
south	-0.366	-0.372	-0.644	-0.565
	(0.419)	(0.410)	(1.144)	(0.896)
voluntary	0.611*	0.613*	1.668	1.574*
	(0.328)	(0.325)	(1.162)	(0.850)
govnonfed	0.753**	0.760**	1.199	1.100
	(0.362)	(0.358)	(1.229)	(0.848)
pov2	-0.337	-0.330	-1.436	-1.416
	(0.545)	(0.545)	(1.673)	(1.500)
pov3	-0.0799	-0.0806	1.767	1.632
	(0.580)	(0.584)	(1.987)	(1.648)
pov4	-1.805**	-1.830**	1.888	1.850
	(0.776)	(0.807)	(3.012)	(2.779)
income2	-1.510***	-1.517***	-0.304	-0.327

	(0.421)	(0.426)	(1.141)	(1.006)
income3	-1.316**	-1.335**	1.297	1.288
	(0.504)	(0.522)	(2.130)	(1.932)
income4	-0.874	-0.886	1.307	1.260
	(0.653)	(0.671)	(2.043)	(1.792)
degree2	-0.158	-0.155	1.369	1.226
	(0.344)	(0.339)	(1.541)	(1.070)
degree3	-0.122	-0.115	2.164	1.923
	(0.505)	(0.499)	(2.475)	(1.549)
degree4	-1.013*	-1.014*	0.693	0.566
	(0.535)	(0.537)	(1.817)	(1.371)
urbanrur1	2.469***	2.491***	2.138	1.949
	(0.906)	(0.930)	(2.294)	(1.757)
urbanrur2	2.055***	2.072***	-0.0285	-0.0362
	(0.727)	(0.748)	(2.044)	(1.858)
urbanrur3	1.453*	1.464*	0.847	0.780
	(0.738)	(0.753)	(1.628)	(1.381)
urbanrur4	0.800	0.816	-0.948	-0.972
	(0.873)	(0.885)	(2.040)	(1.886)
Constant	4.807***	4.797***	3.441	3.643
	(1.449)	(1.451)	(3.282)	(2.696)
Observations	94	94	94	94
R-squared	0.656	0.656		

Table 12: Regression results for the multiple models regressed onto wait times when patient acuity is held constant at the "immediate" level. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Wait Time	(1)	(2)	(3)	(4)
basic_or_full		0.122		-0.230
		(0.107)		(0.556)
basic	0.0664		-0.708	
	(0.116)		(0.758)	
full	0.317**		0.261	
	(0.160)		(0.840)	
age	-0.00389***	-0.00375**	-0.00423***	-0.00370**
	(0.00148)	(0.00150)	(0.00148)	(0.00146)
privres	-0.0107	-0.0166	-0.0637	-0.0566
	(0.114)	(0.112)	(0.171)	(0.136)
nurshome	-0.494**	-0.516**	-0.506*	-0.560**
	(0.205)	(0.208)	(0.268)	(0.232)
homeless	0.0539	0.0429	0.123	0.0640

	(0.455)	(0.471)	(0.431)	(0.481)
male	-0.174***	-0.174***	-0.158***	-0.166***
	(0.0520)	(0.0510)	(0.0537)	(0.0503)
ethun	-0.0670	-0.0665	-0.0676	-0.0661
	(0.111)	(0.110)	(0.132)	(0.118)
white	-0.229	-0.225	-0.245	-0.227
	(0.142)	(0.140)	(0.173)	(0.149)
black	-0.0839	-0.0815	-0.124	-0.101
	(0.158)	(0.156)	(0.187)	(0.167)
asian	-0.360	-0.313	-0.447	-0.286
	(0.227)	(0.236)	(0.286)	(0.256)
pacisland	-0.685**	-0.714**	-0.532	-0.674**
	(0.320)	(0.328)	(0.354)	(0.338)
amerind	-0.325	-0.310	-0.352	-0.299
	(0.377)	(0.358)	(0.447)	(0.359)
paypriv	-0.0426	-0.0471	-0.0588	-0.0639
	(0.0826)	(0.0830)	(0.101)	(0.0877)
paymcare	0.130	0.128	0.114	0.115
	(0.0860)	(0.0862)	(0.0906)	(0.0859)
paymcaid	-0.00132	-0.000467	-0.0658	-0.0359
	(0.0911)	(0.0911)	(0.122)	(0.108)
paywkcmp	-0.203	-0.224	-0.116	-0.210
	(0.245)	(0.250)	(0.274)	(0.263)
payself	0.0561	0.0654	-0.0486	0.0208
	(0.102)	(0.101)	(0.131)	(0.123)
paynochg	0.590**	0.619***	0.525*	0.630***
	(0.230)	(0.221)	(0.315)	(0.236)
payoth	0.0444	0.0478	-0.0149	0.0195
	(0.181)	(0.178)	(0.218)	(0.194)
cebvd	0.219	0.225	0.213	0.232
	(0.238)	(0.236)	(0.236)	(0.225)
chf	-0.188	-0.196	-0.102	-0.159
	(0.127)	(0.126)	(0.154)	(0.140)
eddial	-0.161	-0.175	-0.247	-0.247
	(0.241)	(0.243)	(0.282)	(0.277)
edhiv	0.183	0.201	0.136	0.204
	(0.232)	(0.228)	(0.278)	(0.240)
diabetes	0.141*	0.139*	0.172*	0.154*
	(0.0814)	(0.0831)	(0.0950)	(0.0892)
resint	0.0712	0.0796	0.136	0.130
	(0.135)	(0.133)	(0.201)	(0.164)
msa	0.0880	0.0968	0.274	0.217
	(0.147)	(0.146)	(0.312)	(0.260)
northeast	0.159	0.177	0.173	0.212
	(0.138)	(0.137)	(0.197)	(0.157)
midwest	-0.188	-0.152	-0.228	-0.118

	(0.129)	(0.140)	(0.163)	(0.157)
south	0.133	0.148	0.135	0.175
	(0.117)	(0.117)	(0.167)	(0.133)
voluntary	-0.116	-0.110	-0.155	-0.121
	(0.145)	(0.141)	(0.209)	(0.163)
govnonfed	0.0737	0.114	-0.0664	0.0989
	(0.169)	(0.173)	(0.282)	(0.191)
pov2	-0.0883	-0.0962	-0.121	-0.128
	(0.0829)	(0.0825)	(0.119)	(0.101)
pov3	-0.162*	-0.160*	-0.184*	-0.169*
	(0.0878)	(0.0877)	(0.110)	(0.0984)
pov4	-0.139	-0.119	-0.195	-0.118
	(0.120)	(0.121)	(0.145)	(0.124)
income2	-0.119	-0.0958	-0.195	-0.102
	(0.104)	(0.102)	(0.134)	(0.0970)
income3	-0.250**	-0.227*	-0.267*	-0.198
	(0.119)	(0.122)	(0.151)	(0.139)
income4	-0.302**	-0.282*	-0.342**	-0.272*
	(0.146)	(0.144)	(0.162)	(0.139)
degree2	0.0904	0.0898	0.110	0.1000
	(0.0798)	(0.0818)	(0.0924)	(0.0861)
degree3	0.0262	0.0249	0.0491	0.0357
	(0.0927)	(0.0909)	(0.0984)	(0.0848)
degree4	-0.158	-0.159	-0.213	-0.190
	(0.136)	(0.133)	(0.140)	(0.138)
urbanrur1	0.416***	0.415***	0.436***	0.425***
	(0.155)	(0.154)	(0.159)	(0.147)
urbanrur2	0.307*	0.307*	0.169	0.229
	(0.156)	(0.161)	(0.242)	(0.220)
urbanrur3	0.248*	0.273*	0.0908	0.224
	(0.148)	(0.148)	(0.213)	(0.164)
urbanrur4	0.177	0.157	0.172	0.122
	(0.206)	(0.204)	(0.227)	(0.216)
Constant	3.574***	3.512***	4.027***	3.669***
	(0.301)	(0.292)	(0.505)	(0.390)
Observations	33,942	33,942	33,942	33,942
R-squared	0.080	0.077		0.059

Table 13: Regression results for the multiple models regressed onto wait times when patient acuity is held constant at the "urgent" level. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Wait Time	(1)	(2)	(3)	(4)
basic_or_full		0.0926		-0.0188
		(0.0829)		(0.500)
basic	0.0712		0.419	
	(0.0905)		(0.805)	
full	0.167		-0.312	
	(0.128)		(0.594)	
age	0.00167*	0.00171*	0.00208*	0.00166*
	(0.000952)	(0.000944)	(0.00106)	(0.000963)
privres	-0.0168	-0.0166	0.0132	-0.0362
	(0.0590)	(0.0568)	(0.131)	(0.114)
nurshome	-0.330***	-0.331***	-0.318***	-0.346***
	(0.0854)	(0.0841)	(0.119)	(0.105)
homeless	0.0572	0.0582	0.107	0.0297
	(0.143)	(0.142)	(0.231)	(0.205)
male	-0.0798***	-0.0801***	-0.0801***	-0.0821***
	(0.0184)	(0.0185)	(0.0195)	(0.0178)
ethun	-0.0439	-0.0446	-0.0476	-0.0461
	(0.0783)	(0.0776)	(0.0779)	(0.0786)
white	-0.290***	-0.290***	-0.274***	-0.297***
	(0.0893)	(0.0884)	(0.103)	(0.0899)
black	-0.125	-0.126	-0.126	-0.133
	(0.112)	(0.112)	(0.126)	(0.119)
asian	-0.434***	-0.431***	-0.389**	-0.448***
	(0.130)	(0.129)	(0.170)	(0.143)
pacisland	-0.481**	-0.486**	-0.519**	-0.488**
	(0.226)	(0.227)	(0.260)	(0.228)
amerind	0.0968	0.103	0.193	0.0706
	(0.185)	(0.184)	(0.294)	(0.228)
paypriv	-0.0246	-0.0264	-0.0332	-0.0314
	(0.0469)	(0.0464)	(0.0524)	(0.0514)
paymcare	-0.0910*	-0.0917*	-0.0914*	-0.0951*
	(0.0468)	(0.0468)	(0.0537)	(0.0529)
paymcaid	0.0302	0.0299	0.0374	0.0229
	(0.0472)	(0.0466)	(0.0563)	(0.0496)
paywkcmp	-0.0529	-0.0517	-0.0374	-0.0555
	(0.0930)	(0.0924)	(0.110)	(0.0980)

payself	-0.00429	-0.00463	0.00895	-0.0158
	(0.0675)	(0.0668)	(0.107)	(0.0895)
paynochg	0.335	0.337	0.374	0.322
	(0.233)	(0.233)	(0.245)	(0.228)
payoth	0.0564	0.0542	0.0313	0.0583
	(0.0695)	(0.0694)	(0.0788)	(0.0717)
cebvd	-0.133	-0.131	-0.103	-0.135
	(0.0867)	(0.0851)	(0.0854)	(0.0832)
chf	-0.329***	-0.332***	-0.362***	-0.327***
	(0.0996)	(0.101)	(0.123)	(0.104)
eddial	-0.182*	-0.177*	-0.154	-0.165
	(0.0932)	(0.0922)	(0.108)	(0.110)
edhiv	0.126	0.131	0.161	0.133
	(0.100)	(0.0984)	(0.103)	(0.0965)
diabetes	0.0707*	0.0700*	0.0650*	0.0700*
	(0.0372)	(0.0372)	(0.0389)	(0.0375)
resint	0.300***	0.300***	0.297***	0.300***
	(0.0884)	(0.0871)	(0.0791)	(0.0918)
msa	0.369**	0.371***	0.352*	0.398**
	(0.144)	(0.142)	(0.197)	(0.186)
northeast	-0.106	-0.108	-0.150	-0.0925
	(0.122)	(0.124)	(0.182)	(0.153)
midwest	-0.167*	-0.164	-0.153	-0.157
	(0.0980)	(0.101)	(0.142)	(0.114)
south	-0.0524	-0.0552	-0.0841	-0.0505
	(0.116)	(0.121)	(0.149)	(0.129)
voluntary	0.278***	0.274**	0.233**	0.281***
	(0.106)	(0.106)	(0.114)	(0.103)
govnonfed	0.278*	0.280*	0.292*	0.283*
	(0.161)	(0.160)	(0.168)	(0.162)
pov2	-0.0285	-0.0292	-0.0239	-0.0368
	(0.0526)	(0.0525)	(0.0608)	(0.0595)
pov3	-0.0177	-0.0153	0.00896	-0.0188
	(0.0740)	(0.0734)	(0.0685)	(0.0731)
pov4	0.0743	0.0805	0.135	0.0754
	(0.0770)	(0.0765)	(0.0907)	(0.0768)
income2	0.00452	0.00804	0.0458	0.000638
	(0.0593)	(0.0596)	(0.0953)	(0.0689)
income3	-0.0694	-0.0650	-0.0334	-0.0634
	(0.0798)	(0.0793)	(0.0900)	(0.0810)
income4	-0.139	-0.135	-0.0840	-0.145
	(0.0843)	(0.0838)	(0.134)	(0.0897)
degree2	0.00363	0.00216	-0.0185	0.00861
	(0.0567)	(0.0569)	(0.0637)	(0.0582)
degree3	-0.00221	-0.00453	-0.0258	-0.00213
	(0.0629)	(0.0632)	(0.0649)	(0.0618)

degree4	-0.0632	-0.0638	-0.0638	-0.0665
	(0.0734)	(0.0740)	(0.0848)	(0.0803)
urbanrur1	0.0877	0.0853	0.0554	0.0936
	(0.108)	(0.107)	(0.117)	(0.107)
urbanrur2	0.0989	0.103	0.158	0.0894
	(0.115)	(0.116)	(0.168)	(0.140)
urbanrur3	-0.0376	-0.0307	0.0177	-0.0280
	(0.101)	(0.102)	(0.123)	(0.103)
urbanrur4	0.210**	0.204**	0.176	0.190
	(0.100)	(0.0986)	(0.107)	(0.120)
Constant	3.269***	3.265***	3.150***	3.324***
	(0.253)	(0.251)	(0.489)	(0.392)
Observations	28,815	28,815	28,815	28,815
R-squared	0.067	0.066	0.022	0.064

Table 14: Regression results for the multiple models regressed onto wait times when patient acuity is held constant at the "nonurgent" level. This table shows two OLS models and two IV models. Sampling weights from the 2009 NHAMCS were used to make the estimates nationally representative. Standard errors are present in parentheses. P-values are indicated by the number of stars next to the coefficient value (*** p<0.01, ** p<0.05, * p<0.1).

	OLS	OLS	IV	IV
Wait Time	(1)	(2)	(3)	(4)
basic_or_full		0.0997		0.717
		(0.104)		(0.593)
basic	0.0561		0.991	
	(0.104)		(0.738)	
full	0.389*		1.823	
	(0.219)		(1.401)	
age	0.000187	0.000244	0.00115	0.000891
	(0.00143)	(0.00144)	(0.00193)	(0.00178)
privres	-0.198*	-0.174*	-0.0951	-0.0876
	(0.103)	(0.104)	(0.143)	(0.134)
nurshome	-0.382**	-0.361*	-0.301	-0.291
	(0.184)	(0.183)	(0.205)	(0.187)
homeless	0.214	0.215	0.280	0.255
	(0.209)	(0.208)	(0.305)	(0.262)
male	0.00426	0.00462	0.0173	0.0130
	(0.0436)	(0.0429)	(0.0481)	(0.0437)
ethun	-0.0190	-0.00811	-0.0902	-0.0420
	(0.119)	(0.119)	(0.163)	(0.133)
white	-0.311**	-0.305**	-0.364**	-0.332**
	(0.132)	(0.129)	(0.167)	(0.136)
black	-0.172	-0.167	-0.322	-0.256

	(0.158)	(0.160)	(0.249)	(0.199)
asian	-0.321	-0.317	-0.368	-0.342
	(0.347)	(0.343)	(0.376)	(0.344)
pacisland	-0.554***	-0.572***	-0.741***	-0.704***
	(0.190)	(0.191)	(0.280)	(0.256)
amerind	-0.296*	-0.297*	-0.308*	-0.305*
	(0.152)	(0.153)	(0.183)	(0.169)
paypriv	-8.22e-05	-0.00389	0.124	0.0692
	(0.0974)	(0.0987)	(0.143)	(0.125)
paymcare	-0.160	-0.159	-0.0666	-0.101
	(0.101)	(0.102)	(0.160)	(0.137)
paymcaid	0.132	0.139	0.220*	0.200*
	(0.0843)	(0.0857)	(0.117)	(0.104)
paywkcmp	0.0905	0.102	0.111	0.124
	(0.151)	(0.151)	(0.205)	(0.183)
payself	0.109	0.120	0.269	0.229
	(0.109)	(0.110)	(0.177)	(0.159)
paynochg	0.00377	-0.0126	0.0767	0.0174
	(0.160)	(0.170)	(0.221)	(0.202)
payoth	0.113	0.108	0.0549	0.0676
	(0.188)	(0.185)	(0.183)	(0.177)
cebvd	-0.189	-0.181	-0.195	-0.177
	(0.271)	(0.266)	(0.358)	(0.311)
chf	-0.122	-0.128	-0.0230	-0.0716
	(0.169)	(0.169)	(0.232)	(0.207)
eddial	-0.840*	-0.829	-0.962*	-0.894
	(0.507)	(0.520)	(0.556)	(0.555)
edhiv	0.789**	0.815**	0.816*	0.856**
	(0.397)	(0.399)	(0.428)	(0.412)
diabetes	-0.104	-0.104	-0.0475	-0.0697
	(0.0986)	(0.0988)	(0.111)	(0.104)
resint	0.0161	0.0306	0.167	0.137
	(0.156)	(0.160)	(0.223)	(0.203)
msa	0.443***	0.444***	0.186	0.286
	(0.159)	(0.155)	(0.295)	(0.223)
northeast	0.219	0.235	0.0379	0.138
	(0.164)	(0.163)	(0.262)	(0.192)
midwest	-0.159	-0.143	-0.117	-0.103
	(0.142)	(0.138)	(0.237)	(0.185)
south	0.173	0.168	0.244	0.206
	(0.138)	(0.136)	(0.186)	(0.164)
voluntary	0.347**	0.351**	0.580**	0.499**
	(0.137)	(0.140)	(0.233)	(0.212)
govnonfed	0.478*	0.498*	0.665**	0.631**
	(0.258)	(0.260)	(0.294)	(0.278)
pov2	-0.0348	-0.0394	-0.102	-0.0850

	(0.101)	(0.102)	(0.108)	(0.102)
pov3	-0.0976	-0.0968	-0.105	-0.101
	(0.104)	(0.104)	(0.121)	(0.106)
pov4	-0.0471	-0.0299	-0.102	-0.0479
	(0.144)	(0.150)	(0.182)	(0.159)
income2	0.0236	0.0299	0.0613	0.0590
	(0.0723)	(0.0754)	(0.0896)	(0.0831)
income3	-0.127	-0.129	0.00582	-0.0487
	(0.115)	(0.117)	(0.150)	(0.134)
income4	0.206	0.202	0.374*	0.301*
	(0.147)	(0.149)	(0.216)	(0.180)
degree2	0.146*	0.147*	0.0269	0.0751
	(0.0746)	(0.0747)	(0.112)	(0.0960)
degree3	0.154	0.169	-0.0207	0.0741
	(0.104)	(0.104)	(0.180)	(0.129)
degree4	-0.111	-0.105	-0.188	-0.148
	(0.111)	(0.109)	(0.133)	(0.108)
urbanrur1	-0.0496	-0.0512	-0.207	-0.150
	(0.191)	(0.194)	(0.247)	(0.232)
urbanrur2	-0.248	-0.225	-0.378*	-0.283
	(0.185)	(0.190)	(0.207)	(0.211)
urbanrur3	-0.0313	-0.0215	-0.130	-0.0736
	(0.161)	(0.158)	(0.161)	(0.155)
urbanrur4	0.0839	0.0758	0.301	0.202
	(0.162)	(0.161)	(0.282)	(0.213)
Constant	3.048***	2.990***	2.525***	2.614***
	(0.267)	(0.277)	(0.499)	(0.443)
Observations	33,747	33,747	33,747	33,747
R-squared	0.128	0.124		0.070