

**UCLA**

**UCLA Electronic Theses and Dissertations**

**Title**

Adoption of Electronic Health Records by Physicians for Use in their Practices

**Permalink**

<https://escholarship.org/uc/item/0ns6m77n>

**Author**

Balgrosky, Jean Ann

**Publication Date**

2015

Peer reviewed|Thesis/dissertation

UNIVERSITY OF CALIFORNIA

Los Angeles

Adoption of Electronic Health Records

by Physicians for Use in Their Practices

A dissertation submitted in partial satisfaction of the

requirements for the degree Doctor of Philosophy

in Health Services

by

Jean Ann Balgrosky

2015

© Copyright by

Jean Ann Balgrosky

2015

ABSTRACT OF THE DISSERTATION

Adoption of Electronic Health Records

by Office-Based Physicians for Use in Their Practices

by

Jean Ann Balgrosky

Doctor of Philosophy in Health Services

University of California, Los Angeles, 2015

Professor Jack Needleman, Chair

Despite high levels of investment, expectation, and effort to push forward the adoption of Electronic Health Records (EHR) nationally, challenges for physicians in doing so and slow rates of adoption persist. However, the great promise of EHR—improved quality and cost performance of health care—depends on physician use of EHR systems. This study aims to

provide findings and recommendations to inform research and policy regarding EHR adoption by physicians for use in their practices.

The data source for this study is the Center for Studying Health System Change (HCS) and Community Tracking Study (CTS) Physician Survey, Round 3 (2000–2001) and Round 4 (2004–2005). The theoretical anchor is Rodgers' Diffusion of Technology Theory (Rogers, 1962, 1981).

The methods employed in this study include descriptive statistics, Cronbach's Alpha, sub-scale tests, Exploratory Factor analysis, and Guttman scaling, regression, difference-in-differences analysis, cross-sectional analyses and others statistical methods.

The findings are as summarized: 1) Though small and medium/large practices increased their use of EHRs over the period, small practices increased at a lower rate, thus the gap in EHR adoption rates between small and medium/large practices increased over the study period. 2) Small and medium/large practices are de-adopting EHR functionality over time, a finding not noted before. However, this de-adoption is muted by the overall net increase in adoption scores over time. 3) Characteristics associated with lower adoption include: female, non-white, in oldest groups, and small practices. Managed care as a source of revenue for physician practices was associated with increased EHR adoption.

The dissertation of Jean Ann Balgrosky is approved.

Douglas Bell

Paul R. Torrens

Frederick Zimmerman

Jack Needleman, Committee Chair

University of California, Los Angeles

2015

## DEDICATION

It is with deep gratitude and love that I dedicate this book:

To my family, Parker, Melissa, Jessica, Seth, Sarah, Wyatt, CJ, and Steven. Thank you for your unending support and enthusiasm for my pursuit of a PhD. Without you, none of this matters.

To my parents, Steven A. Balgrosky and Evelyn Margaret Cook Balgrosky—how I wish I could share this with you. Somehow I know I am. Thank you for your wonderful love, and for teaching me a love of learning and perseverance.

To my sister, Wendy, and brother, Steve — you are my rocks, and your love and support bring great comfort to me.

To my grandparents, Aleksandr Balgrosky and Xenia Bakkan Balgrosky—for your love and courage in bearing great hardship to leave your homeland and build a new life for your family in this country.

To my grandparents, Elmer Christian Cook and Adele Harriet Muellman Cook—for your love, strength of character, and devotion to helping your family build good lives.

To my grandchildren, Katie, Jackson, Ace, Jesse, Nina, Scott, Maya, Max, Stella, and those yet to come—you are the great reward of life. I hope this dissertation inspires you to pursue your dreams, whatever they might be.

To Olive Johnson, a woman before her time—who taught me the foundation for my career in the discipline of health information systems and technology, and helped me at a difficult time in my life to pursue my graduate education in this field. Thank you for devoting your life to the education of students like me. I hope I made you proud.

## TABLE OF CONTENTS

- I. Chapter 1 – Introduction and Background, 1
- II. Chapter 2 – Background and Literature Review, 10
- III. Chapter 3 – Measuring Electronic Health Record Adoption: Development of the Dependent Variable, 22
  - a. Table 3-1: Factor loadings (pattern matrix) and unique variance: 7 computer-use variables, 45
  - b. Table 3-2: Factor result, 46
  - c. Table 3-3: Cronbach’s Alpha Reliability Statistics, 46
  - d. Table 3-4a: Matrix of tetrachoric correlations among IT computer-use variables 2000–2001, 47
  - e. Table 3-4b: Matrix of tetrachoric correlations among IT computer-use variables 2004–2005, 48
  - f. Table 3-5: Percentages of installations with each IT variable in combination with least used IT capability: “*Use of the computer to write prescriptions*”, 49
- IV. Chapter 4 – Changes in Electronic Health Record Adoption by Physicians for Use in Small and Medium/Large Practices During a Period of National Policy Intervention, 50
  - a. Figure 4-1 Physician & Practice Characteristics in Relation to IT Adoption, 55
  - b. Figure 4-2: IT Functionality Changes over Time in the Pooled Sample, 72



- c. Table 4-1: Descriptive statistics from surveys of small and medium/large physician practices regarding use of electronic health records (EHR). CSHSC: CTS Round 1: 2000–2001, Round 2: 2004–2005, 76
  - d. Table 4-2: Difference-in-differences (DID) model of the effect of policy on use of electronic health records (EHR) by small and medium/large physician practices: CSHSC CTS: 2000–2001, 2004–2005, 77
  - e. Table 4-3: Post-estimation Difference-in-differences (DID) Bootstrap, 78
  - f. Table 4-4: Post-estimation predicted means pre- and post policy intervention IT Adoption Scores for small and med/large practices: CSHSC; 2000–2001, 2004–2005, 78
  - g. Table 4-5: Post-estimation difference-in-differences (DID) between small and medium/large physician Time 1 (2000–2001) and Time 2 (2004–2005), 78
- V. Chapter 5 – Panel Analysis of Physician Adoption of Electronic Health Record Capabilities, 79
- a. Figure 5-1: Conceptual Model of Physician Panel Analysis 2000–2001 and 2004–2005, 85
  - b. Table 5-1: Descriptive Statistics of Physician Panel 2000–2001 – 2004–2005 Panel Sample\*(N = 3,164), 132
  - c. Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians 2000–2001 – 2004–2005 Full Panel Sample, 133

- d. Table 5-3: Trend in averages in use of EHR by full sample, small, and medium/large physician practices among panel over time (2000–2001 – 2004–2005), 134
  - e. Table 5-4: Changes in IT Adoption Scores among all practices: addition, retention, or reduction of EHR functionality among full panel physicians 2000–2001 – 2004–2005, 135
  - f. Table 5-4a: Changes in IT Adoption Scores among small practices: addition, retention, or reduction of EHR functionality among full panel physicians 2000–2001 – 2004–2005, 136
  - g. Table 5-4b: Changes in IT Adoption Scores among medium/large practices: addition, retention, or reduction of EHR functionality among full panel physicians 2000–2001 – 2004–2005, 137
  - h. Table 5-5: Linear regression model of change in total IT Adoption Score for full panel and stratified by practice size (Small and Medium/Large Practices), 138
  - i. Table 5-6: IT Adoption among panel physicians and interaction with physician and practice characteristics for 2000–2001, 2004–2005, and Full Panel, 139
- VI. Chapter 6 – Conclusion, 140
- VII. References, 156

## ACKNOWLEDGEMENTS

I am indebted to the tireless, patient work of my dissertation committee; they have taken the time to authentically be interested in this work and see the value of the information contained within it. To Dr. Jack Needleman, I extend heartfelt thanks for paving the way and sharing his knowledge of the research process as well as my zeal for this topic, and offering his expertise and ability. To Dr. Paul Torrens, my long-time mentor and friend who shares my respect for the earlier days of medical record science at the UCLA School of Public Health, and whose guidance and encouragement has sustained me through the years. To Dr. Doug Bell, whose tremendous expertise in health information technology and research he contributes constructively and generously, making the finished product that much better. To Dr. Fred Zimmerman, whose sharp analytical thinking pierces through the mountain of ideas that a dissertation can become, to focus on the essence of what's most important and how to communicate that clearly. Thank you all so very much. I have truly enjoyed working with you on this dissertation, am in awe of your expertise, and deeply appreciate your contribution to this work—the end product is vastly better for you having been on my committee.

I owe deep gratitude to my long-time mentor and friend, Dr. Jonathan Fielding—thank you for welcoming me back to the Fielding School of Public Health with enthusiasm, so that I could finish my PhD after taking time to build my career and my family. Your unending guidance and encouragement have made this school my academic home. You inspire me.

I am deeply grateful to my friend and colleague, Dr. Neetu Chawla, for your support and friendship through the big push to get this dissertation completed. You have been with me every step of the way.

I extend my profound thanks to my friend and colleague, Jessie Chatigny, who has patiently and earnestly provided support and answers to many editing questions throughout the writing of this dissertation.

## VITA

### **Jean Balgrosky**

Having devoted my professional career to health care, over 20 of those years have been spent as a chief information officer (CIO), with other health information and technology roles leading up to that. My passion is innovation through the effective and creative use of health information technology (IT). In leading and implementing systems initiatives, my goal is to develop new ways to use IT to help providers and advance the vision and strategies of an organization. Currently completing my Ph.D. in Health Services, my goal is to continue to improve the field of health care through health IT research, teaching, and writing to share what I have learned by doing over the years. I am Founder of Bootstrap Incubation, a company dedicated to growing innovative information technology businesses in life science and health care. My philosophy is to create a supportive educational and professional environment that inspires people's confidence and encourages them to use their talents to realize their fullest potential. In terms of key achievements, I was responsible for the design and implementation of strategic HIT plans for two large multi-hospital systems, Holy Cross Health System (now Trinity Health) 13-hospital Catholic multi-hospital system; and Scripps Health, a large integrated delivery system in San Diego, where I led the implementation of a comprehensive electronic health record (EHR).

### **EDUCATION**

- 2015 University of California, Los Angeles, Ph.D. candidate, anticipated completion of Ph.D. in Health Services in Spring 2015.** UCLA Fielding School of Public Health - Health Policy and Management. Dissertation topic: "Adoption of Health Information Technology by Physicians for Use in their Practices."
- 1980 University of California, Los Angeles Master of Public Health,** Management of Health Information Systems
- 1974 University of California, Los Angeles, Bachelor of Science, Magna Cum Laude,** Public Health/Health Services, with specialization in Medical Record Science.

### **SIGNIFICANT ACCOMPLISHMENTS**

- Author of the textbook, *Essentials of Health Information Systems and Technology*, published in August, 2014 as part of the Essentials of Public Health Series published by Jones and Bartlett Learning. *Essentials of Health Information Systems and Technology* targets an audience of students of schools of public health at graduate and upper undergraduate levels. Published August 12, 2014.

- As CIO of MD Revolution, developing a personalized digital health platform combining data from a variety of sources, such as mobile devices, electronic health records, and genetic data - for use by individuals, physician practices, and health systems in support of Accountable Health Organizations, population health initiatives, chronic care management, corporate wellness programs, and care management processes. Connecting providers and patients, and engaging patients in the management of their own health, the platform provides continuous data monitoring, sophisticated algorithms, and machine learning to engage patients, connect them with their providers, and help track and manage chronic disease, risk factors, and improve health.
- Founded Bootstrap Incubation, LLC, supporting, mentoring, investing in, and growing numerous portfolio companies that innovate in health care, life sciences, cloud computing, and data analytics.
- Created a patient-centric IT platform for implementing the electronic health record (EHR) system, including master patient index system for ten years of patient data (2.1 million records) and integration across five hospitals, 14 clinics, 2,600 physicians, and home health services.

## PROFESSIONAL EXPERIENCE

- 2007–Present* UCLA Fielding School of Public Health, Department of Health Policy and Management, Los Angeles, California. *Instructor, Lecturer, and Special Reader*
- 2011–Present* Bootstrap Incubation, LLC, San Diego, California. *Co-Founder and CIO*
- 2005–Present* MD Revolution, San Diego, California. *CIO and Board Member*
- 1997–2005* Scripps Health, San Diego, California. *Senior Vice President and CIO*
- 1986–1997* Holy Cross Health System Corporation, South Bend, Indiana. *Vice President of Information Resources*
- 1983–1986* Community Hospitals of Indianapolis, Inc., Indianapolis, Indiana. *Director of Information Management*
- 1982–1983* Peat, Marwick, Mitchell & Co., Los Angeles, California. *Senior Consultant in Systems Management Group Healthcare*
- 1980–1982* Lutheran Hospital Society of Southern California, Los Angeles, California  
*Research Associate*

# Adoption of Electronic Health Records by Physicians for Use in Their Practices

## Chapter One

### Introduction and Background

The pursuit of adoption of Electronic Health Records (EHRs) has captured the attention of health services providers across the nation, including physicians implementing EHRs for use in their practices (Bates, 2005) (DesRoches C. , et al., 2008). While EHR adoption has been a goal for many years (Institute of Medicine, 1991) (Committee on Quality of Health Care in America, Institute of Medicine, 2001), rates of adoption have been low among providers EHR adoption, estimated in 2009 at 10% within physician practices and 17% within hospitals and (Blumenthal D. M., 2009). The percentage of office-based physicians using a basic EHR system increased from 3.8% in 2007 to 23.5% in 2012 (Hsiao, Hing, & Ashman, No. 75, 2014). During the same time period, small practices lagged behind larger practices in the use of any type of EHR system by a sizable gap; for instance, in 2007, EHR usage was 20.6% among solo practitioners compared to 74.3% physicians in practices with 11 or more physicians. (Hsiao, Hing, & Ashman, No. 75, 2014)

With added emphasis on improving quality and cost performance in health care, the U.S. government set the implementation of EHRs as a priority with direction-setting visions of EHRs

for all people in the US by 2014 from both George W. Bush and Barack Obama; George W. Bush signed an executive order titled the “President’s Health Information Technology Plan”, calling for a 10-year plan to have health records on-line for all Americans (Bush, 2004). President Barack Obama further magnified this goal in 2009 with the enactment of the HITECH Act: “Our recovery plan will invest in electronic health records and new technology that will reduce errors, bring down costs, ensure privacy, and save lives” (Obama, 2009). This topic gained immense action at the national level through the implementation of the Health Information Technology for Economic and Clinical Health (HITECH) Act as part of the American Recovery and Reinvestment Act (ARRA) of 2009 (US Department of Health and Human Services, 2009). The HITECH Act allocated \$36.2 billion, to stimulate the adoption of health information technology including investment of \$34.2 billion in incentive payments to providers for “Meaningful Use” of EHRs and \$2 billion in grants and loans to advance health information technology through training programs, demonstration projects, technical assistance and other activities such as development of “Meaningful Use”, technical and data standards (CMS Office of Public Affairs, 2010). Beyond the impetus this legislation provides, persistent problems in healthcare quality and efficiency, increasing use of on-line health sources by patients and providers (Abreu, 2006), and automation of most forms of modern commerce have fueled adoption of EHRs as a priority for providers, patients and payers for the past several decades. For example, among seniors, 71% go on-line every day and 67% want to access health services from home. (January 15, 2013 Health Online 2013 Susannah Fox and Maeve Duggan <http://www.pewinternet.org/2013/01/15/health-online-2013/>) Society has dramatically increased its use of the Internet for health-related purposes to the point where the majority (71%)



of people in the U.S. use Internet sources when seeking healthcare-related information (Abreu, 2006).

Major impetus for the HITECH Act and the government's program to stimulate adoption of EHRs by physicians came when The Institutes of Medicine's watershed reports "To Err Is Human" and "Crossing the Quality Chasm" sounded a clarion call and documented the unacceptably high avoidable medical error rates in U.S. hospitals and the need to improve quality of care through several methods, including increased use of health information technology (HIT) and EHRs (Committee on Quality of Health Care in America Institute of Medicine, 1999) (Committee on Quality of Health Care in America, Institute of Medicine, 2001). Through this time period, we may have reached a tipping-point in adoption of healthcare information technology and EHRs, and physicians' practices are an important part of that evolution (Robert Wood Johnson Foundation, 2008) (Office of the National Coordinator, 2010)

Growing provider, payer, government, and consumer expectations for improvements in quality, cost reductions, patient-focused service, and efficacious processes push healthcare providers and organizations, the government, and suppliers to keep pace. Anticipated EHR benefits such as enabling reductions in medication errors and improvements in efficiency and effectiveness of care cause these information technology tools to be seen as essential to improving health care services (Evans, Nichol, & Perlin, 2006) (Ref. 2013 find). In addition to the long-standing tradition of the practice of medicine by physicians in office-based settings, during this time period health care reform is driving increasing percentages of care from acute care to ambulatory settings ( (Johnson, 2009) (Ref. 2015). The majority of primary care visits take place in physician offices; in 2008, 84 % of 664.0 million such visits were to office-based, non-federally employed physicians (Hing & Uddin, 2010). Of the 83% of adults with a usual place of care,

74% considered it to be a doctor's office or health maintenance organization (HMO) (Blackwell, Lucas, & Clarke, 2014). Because of the importance of office-based physician practices to the fabric of U.S. health care, it behooves us to understand characteristics associated with EHR adoption within these practices, and further to understand differences that exist between small and medium/large practices in using these important tools.

Physician practices are among the organizations with perhaps the greatest potential for improving overall quality and cost performance in the US healthcare delivery system. But to date, depending on the study and the definition it uses for EHR, research shows as of 2008 only 4 percent of physicians have adopted fully functional EHR system and 13% percent a basic one (DesRoches C. , et al., 2008). Most EHR implementation activity focused in hospital settings; adoption rates in physician practices are estimated about 10% vs. hospitals at about 19 % (Hing, Burt, & Woodwell, 2007) and 6% for full EHRs and 21% for basic EHRs in physician offices (Office of the National Coordinator, 2010). In general, physician practices of fewer than five (5) physicians have the lower EHR adoption rates (Hing, Burt, & Woodwell, Electronic Medical Record Use by Office-Based Physicians and Their Practices: United States, 2006, 2007). Larger practices and hospitals, with greater volumes and varieties of services to generate revenues, hospitals have greater access than physician practices to capital, administrative and support capacity to sustain implementation efforts, as well as IT staff to provide ongoing support.

But the promise of health information technology to improve health care quality and control costs versus the reality of implementations often disappoints those investing in these computer systems (Bates, 2005). Further, EHR products now available are unlikely to achieve full diffusion in a critical market segment within the time frame being targeted by policy makers (Ford, Menachemi, & Phillips, 2006). Pointing out that adoption is happening at too slow a rate

to accomplish stated policy goals of widespread adoption by 2014, it was reported by Ford et al, closely following Bush's announcement in support of EHR adoption, that EHR adoption, especially in small practices of 10 or under, is at a lower than desired rate (Ford, Menachemi, & Phillips, 2006). This dissertation study aims to inform EHR adoption among office-based physicians, particularly differences between small and larger practices, through the analysis of physician and physician practice characteristics associated with EHR adoption.

In many cases, EHR implementations do not achieve intended benefits although major investments have been made or those benefits are ambiguous (Chaudry, et al., 2006). For an EHR to reach its potential beneficial effect in a physician practice, initial basic adoption must occur, then a gradual process of refinement and adjustment takes place to hone the use of the system; the practice must establish achievable objectives for adopting EHR functionality in the practice, then measure progress towards and realize the intended benefits, such as medication error reduction or efficiency improvements. As long as basic adoption remains the focus, higher level, more focused refinements must wait. By understanding what characteristics are associated with adoption, those predictors can be brought to bear on practices lacking them, to assist in their EHR adoption preparing them for further achievement of benefits and the promise of EHRs.

Slow rates of adoption are attributed to factors such as misaligned incentives, providers' lack of capital and operating resources, lack of standards in EHR products and services (Middleton, Hammond, Brennan, & Cooper, 2005) and resulting workflow that hampers physician productivity rather than helping them be more efficient, at least initially (Poon et al, 2006).

Research has shown that providing financial incentives, especially to smaller practices, is necessary to accelerate adoption (DesRoches C. , et al., 2008). Now that the U.S. government is providing financial incentives and penalties through HITECH, what else needs to be understood

in order to improve EHR adoption and by extension, the role of office-based physician and the viability of their practices?

Diffusion of EHR information technology into healthcare is a complex undertaking, with numerous dimensions associated with such implementations (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). Also, as is often stated, the US healthcare system is very complex, which is, in fact, one of several reasons why EHRs are desired in the first place (Brailer, 2005). But it stands to reason that automating health care is even more complex than health care itself, especially if one of the goals of such automation is to simplify processes, i.e., EHR technology is used with the expectation that it will simplify something that in many instances is beyond its control and in attempting to do so, is going against the grain of long-standing paper-based processes, fashioned primarily on an assembly line model - “(Process) Redesign asks the team members, especially the insiders, to suspend their belief in the rules, procedures, and values that they’ve honored their whole working lives” (Hammer & Champy, 2001). Being caught in a world today that is part paper-process and part electronic, while progress along other fronts of innovation (such as pharmaceuticals and technology) speeds along, health care providers face many coordination challenges. For example, increasing numbers and varieties of pharmaceuticals taken by many patients are outstripping our current minimal ability to track and monitor these lists of medications, causing potentially serious harm to patients (CBS news story, 2011). Addressing this type of problem requires full-scale coordinated change across thousands of provider settings – and the promised benefits of EHRs are seen as pivotal to this needed change (Blumenthal D. M., 2009).

Thus difficulty and a measure of disorientation reign in attempts to understand how to achieve benefits associated with EHRs; doing so requires we improve EHR adoption rates in physician

practices, as well as learn how to use, interpret and manage EHRs to our individual and collective advantage in the delivery of health care services. To encourage adoption, it would be helpful to understand ways to better support physicians in their attempts to adopt EHRs into their busy practices. Factors such as financial capacity, productivity, technical, privacy, and leadership have been identified by several studies as predictors or barriers to EHR adoption (DesRoches C. , et al., 2008) (Menachemi N. , 2006). EHR adoption studies that have been conducted to date recommend focusing on practice-level barriers to adoption (Grant R. , Campbell, Gruen, Ferris, & Blumenthal, 2006) and policy-level initiatives to stimulate such adoption (Blumenthal D. M., 2009) (Castillo, Martinez-Garcia, & Pulido, 2010) (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015). This study aims to identify practice-level predictors of EHR adoption by physicians for use in their practices, and elucidate differences between early adopters and later adopters in order to clearly define ways to facilitate such adoption, given the sense of urgency associated with obtaining associated incentives and benefits to improve our health system.

This study uses data collected through a national survey of physicians conducted by Center for Studying Health System Change (HCS) and Community Tracking Study (CTS) Physician Survey, accessed through Inter-university Consortium for Political and Social Research (ICSPR) (Center for Studying Health System Change, 2003) (Center for Studying Health System Change, 2006). The study is designed with the intention that by bringing light to physician and practice predictors of EHR adoption, insights into ways to effectively support and stimulate adoption can be developed and applied to policy and management techniques. Anchored in Rogers' Diffusion of Technology Theory (Rogers, 1981), the study will examine trends in these predictive characteristics over time, so that changes in policy and methods of support can be specified and

anticipated as adoption matures and becomes more widespread. Studies indicate that the characteristics of very early adopting physicians and physician practices (innovators) will differ from those adopting these systems later (DesRoches et al, 2008) (Menachemi N. , 2006), thus supporting the need to study trends and changes in predictors as progress along the EHR adoption curve matures.

To assist the goal of broad-based, effective EHR adoption, this dissertation analyzes and takes steps toward clarifying the relationship between specifics of physicians and their practices and their adoption of EHRs; it also analyzes changes in the characteristics associated with adoption over time and according to Rogers' phases of technology diffusion. Finally, the study provides a framework for identifying and organizing key factors in EHR implementations and adoption, and provides recommendations assisting policy and organization of support resources.

This study uses multiple rounds of data from a nationwide survey of a random sample from the population of U.S. physician practices. It is an opportunity to evaluate predictors of adoption across a large national sample of physician practices, with detailed physician, practice and financial/practice revenue data to answer the question: what are those physician or practice factors that predict successful EMR adoption so that policy and support initiatives and implementation strategies can be based on that knowledge? The study will:

1. identify practice or physician characteristics that most strongly predict EHR adoption, taking practice size into consideration as a proxy for sufficient infrastructure and support resource availability to sustain an implementation successfully;
2. evaluate trends in those predictors over time, comparing 2000–2001 and 2004–2005 rounds, and interpreting results according to Rogers' Adoption Curve; and

3. develop a conceptual framework for identifying specific factors involved in EHR implementation to facilitate EHR adoption by physicians for use in their practices, thus adding to the literature in this area.

This dissertation proposes to study the use of information technology in healthcare by examining predictors associated with EHR adoption by physicians in their practices, and asks whether practice characteristics have an independent effect, beyond individual physician characteristics. This will be accomplished through the analysis of survey data about the use of computers (i.e., EHR functionality) by physicians in their practices, with the aim of shedding light on characteristics of physicians and physician practices adopting EHRs for use in their practices. The study also presents a framework to describe and demystify what is important to the adoption of health information technology by physicians for use in their practices. This is done in the hope that further understanding about information technology's use in healthcare can bring good to patients and progress to physicians in their practices.

Adoption of Electronic Health Records  
by Physicians for Use in Their Practices

Chapter 2

Bibliography and Literature Review

**Literature Review**

The literature contains a growing number of studies regarding EHRs, their adoption, predictors and barriers to that adoption, with many references to but little empirical research studying Roger's Diffusion of Technology Theory.

For this proposal, there are four categories to the literature review:

- I. Electronic Health Records (EHR)/Health Information Technology (HIT)
- II. Adoption of EHRs by physicians/physician practices/ambulatory settings
- III. Diffusion of Innovations
- IV. Barriers and predictors of adoption

*Electronic Health Records*

The adoption of Electronic Health Records (EHRs) has been a goal among many healthcare organizations for physicians for use in their practices for several decades (Institute of Medicine,



1991). The Institutes of Medicine definitively described the functional content of an EHR in 2003:

An EHR system includes (1) longitudinal collection of electronic health information for and about persons, where health information is defined as information pertaining to the health of an individual or health care provided to an individual; (2) immediate electronic access to person- and population-level information by authorized, and only authorized, users; (3) provision of knowledge and decision-support that enhance the quality, safety, and efficiency of patient care; and (4) support of efficient processes for health care delivery. Critical building blocks of an EHR system are the electronic health records (EHR) maintained by providers (e.g., hospitals, nursing homes, ambulatory settings) and by individuals (also called personal health records)” (Committee on Data Standards for Patient Safety Institute of Medicine, 2003).

Since this earlier definition, important contributions have been made to the ability to study EHRs by identifying more specific definitions of the content of EHR implementations, namely, Basic EHRs (including health information and data, e-prescriptions, and results viewing) or Fully Functional EHRs (including Basic functionality plus order-entry and results management, and clinical-decision support) (DesRoches C. , et al., 2008) (Hsiao, Hing, Socey, & Cai, 2010). The National Ambulatory Medical Care Survey (NAMCS) also developed a more specific set of definitions for Partial EHRs (part paper), Full EHRs (general use) and Comprehensive EHRs (in addition to general use, including prescription orders, clinical decision support and imaging results). The comprehensive EHR adoption rate is not changing significantly from year to year, while the use of full or partial EHR systems is increasing (Hing, Burt, & Woodwell, 2007). These definitions greatly help researchers detect different levels of EHR adoption in ambulatory and office-based settings of care, but current literature varies widely in approaches to measuring EHR adoption (Hirsch, 2015).

Focusing on improving the quality of care, President George W. Bush called for electronic health records (EHRs) for all Americans by the year 2014 (Bush, 2004) (Bernstein & Broccolo, 2006). EHRs have been associated with anticipation of many benefits clinically (quality improvement and reduced medical errors), financially (process efficiency and cost control), and from public health and national security standpoints (bio-surveillance, large scale immunization campaigns), and that their benefits would exceed their costs (The Lewin Group, 2005). The U.S. government launched initiatives labeled “e-health” (Monegain, 2004) and more recently major initiatives by the Obama administration for computerizing patient health records with the goals to reduce medical errors, gain administrative efficiencies, and improve clinical outcomes in our health delivery system, as well as create jobs (Obama jobs creation and electronic medical records in healthcare, 2009) (Goldman, 2009). The American Recovery and Reinvestment Act of 2009 (ARRA) included the Health Information Technology Economic and Clinical Health Act, allocating \$36 Billion for incentives for physician practices and hospitals to adopt EHR systems meeting Meaningful Use Criteria in three stages of gradually increasing comprehensive functionality (Blumenthal D. M., 2009) (Centers for Medicare and Medicaid Services, 2010).

In spite of all the attention and effort over the past decades, anticipated benefits of EHRs have been underachieved in many cases, are ambiguous in research findings, and have resulted in unintended consequences that are just beginning to be understood (Menachemi N. , 2006) (Bloomrosen, Starren, Lorenzi, Ash, Patel, & Shortliffe, 2011) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012). Moreover, many of the benefits achieved through the use of EHRs are gains experienced by payers, not physicians who implement and pay for the EHRs (Brailer, 2005). Overall, positive benefits are occurring through the adoption of EHRs, with much to learn about the specific relationship of EHR functionalities

to process and outcomes, and clarity around the costs and benefits of EHRs (Buntin, Burke, Hoalgin, & Blumenthal, 2011) (Goldzweig, Towfigh, Maglione, & Shekelle, 2009). While the potential is still there, we lack information about the effect of EHRs on clinical care (Hsu, 2008), although there is agreement on high priority areas of improving patient/consumer health, improving clinical decision-making, improving communication, improving organizational quality and efficiency, and improving public health (Jha, et al., 2003). Thus, while achievement of the multiplicity of EHR benefits largely eludes health care systems in the United States, the potential persists (Buntin, Burke, Hoalgin, & Blumenthal, 2011).

Originally, EHR systems were developed in-house, thus were predominantly developed in larger hospitals with sufficient capital and operating budgets and staffing to afford such development projects (Goldzweig, Towfigh, Maglione, & Shekelle, 2009). Vendor software products have been available since 1980s, but not much is known about the performance and effects of commercially available technology in ambulatory settings although potential is shown for improved coordination of care in one large integrated delivery system (Hsu, 2008). Significant investments of time and money are required for acquisition, implementation and on-going support of EHRs, a fact that contributes to their low adoption rates (Goldman, 2009).

### *EHR Adoption*

Most meaningful adoption of EHRs, now and historically, has occurred in original developing hospitals and large practices with staff and culture built around EHR-supported processes, with sustained efforts lasting many years (Goldzweig, Towfigh, Maglione, & Shekelle, 2009).

Implementation of EHRs is more challenging for physician practices than hospitals due to resource and capacity constraints of these smaller organizations (Hing, Burt, & Woodwell,

2007). Particular challenges exist in pursuing the goal of widespread EHR adoption due to the challenges associated with EHR adoption in small organizations. Among all practices in the U.S. 2004, 69.2% of physician practices consisted of solo practitioners (including 35.8% of office-based physicians) (Hing & Burt, 2007). Considering the fact that so many practices are small (less than five (5) physicians) or solo, the strong relationship between practice size and adoption of EHRs is a glaring issue, notwithstanding the benefits that can be achieved by small practices with EHR adoption (Bates, 2005) (Miller, West, Brown, Sim, & Ganchoff, The Value Of Electronic Health Records In Solo Or Small Group Practices, 2005). Given these challenges, widespread adoption of EHRs in small practice settings using currently available commercial products is estimated to not be achievable before 2024 (Ford, Menachemi, & Phillips, 2006). Continuous assessment of EHR adoption rates reveals gradual progress, although that progress is slower than originally anticipated, especially for smaller practices (Burke-Bebee, 2008) (DesRoches C. , et al., 2008) (DesRoches C. M., 2015). The general shift in health services delivery from in-patient to ambulatory care plus added demands placed on the system through health care reform aimed at reducing the number of uninsured persons exacerbates this issue, requiring greater efficiencies if increasing needs for care in these settings, including physician practices, are to be met (Johnson, 2009).

The number of empirical studies published in the literature on various facets of EHR adoption is growing, but little insight tying benefits to the significant investments being made in these systems, the high expectations of results, and risks physician practices face in their implementations. Recent survey results show that 55% of physicians do not plan to attest to Meaningful Use Stage 2 in 2015, clear evidence that the road to widespread EHR adoption physicians for use in their offices is a long one (Blumenthal & Tavenner, 2010) (HITC Staff,

2015). Research using consistent metrics and measurement of EHR adoption beyond self-reporting are needed to help us better understand the specifics of EHR adoption in relation to physician and practice characteristics as we seek ways to bolster such adoption (Li, 2011) (Castillo, Martinez-Garcia, & Pulido, 2010) (Cleary & Jette, 1984).

Published studies using a variety of measures and approaches to studying these rates indicate EHR adoption rates are consistently slow and low, as evidenced by the following examples (Jha, et al., 2006) (DesRoches C. , et al., 2008) (DesRoches C. M., 2015) (Shilling, 2011). Recent EHR adoption rates in the ambulatory care environment are: just over 10 percent (Morton, 2009); range from 9% to 29% based on measuring fully functional or basic EHRs (DesRoches C. , et al., 2008); are approximately 23.9 percent (Jha, et al., 2006); 21% for basic EHRs in physician offices and 6% for full EHRs in physician offices (Office of the National Coordinator, 2010); less than 2% of physicians in solo or two-physician practices reported a fully functional EHR and 5% reported a basic EHR versus 13% adoption in larger groups (Rao, DesRoches, Donelan, Campbell, Miralles, & Jha, Electronic health records in small physician practices: availability, use, and perceived benefits, 2011); 54% of physicians reported their practices had adopted an EHR system in 2011, and three-fourths of those EHR systems met Meaningful Use criteria (Jamoom, Beatty, Bercovitz, Woodwell, Palso, & Rechtsteiner, 2012); and 3.8% fully functional EHR in 2007, similar to the 2006 percentage of 3.1% (Hing & Hsiou, 2007). Perhaps equally revealing are multiple findings that primary care physicians are less likely than other medical practitioners to use EHRs (Menachemi & Brooks, 2006); that physicians treating Hispanics were less likely to be using a comprehensive EHR (Chenghui & West-Strum, 2010); and that among primary care providers in a rural area (Kentucky) adoption was variable, with

only 43% having dial-up service, although interest is high (71%) in an EHR among primary care providers (Andrews, Pearch, Ireson, & Love, 2004).

Literature is also limited but growing in the area of reasons for success or failure of EHR adoption in physician practices. While most literature relates to descriptive surveys and statistics (DesRoches C. , et al., 2008) (The International Council on Medical and Care Computetics, 2006), some studies describe financial barriers and incentives as primary predictors of EHR adoption (Hing, Burt, & Woodwell, 2007) (Menachemi N. , 2006) (Hing & Hsiou, 2007); critical factors for adopting EHRs including user attitude towards information systems, workflow impact, interoperability, technical support, communication among users, and expert support (Castillo, Martinez-Garcia, & Pulido, 2010); and attitudes affecting EHR adoption, primarily lack of user acceptance (Morton, 2009). Barriers and predictors of adoption are identified (Menachemi N. , 2006) and are discussed below in a separate section.

### *Diffusion of Innovation/Technology*

Widely cited in literature regarding EHR adoption, Rogers' Diffusion of Innovation Theory and Adoption Curve provides a theoretical backdrop to this dissertation study by describing the phases of diffusion and thus adoption of any new technology (Rogers, 1981) (see Rogers' diagram pp. 12, 13). Rogers' book, *Diffusion of Innovations* describes four (4) elements that shape the spread of a new thought or design: innovation, communication channels, time, and a social system. During this process of assimilation, people evolve through five (5) phases: knowledge, persuasion, decision, implementation and confirmation (Rogers, 1981) (*Diffusion of Innovations*, 2011).

While often cited in literature on EHR adoption and other innovations (Chaudry, et al., 2006), very few empirical studies apply Rogers' diffusion theory and adoption curve to health care in a systemic way; most studies limit the unit of adoption to the individual and the diffusion process is assumed to happen through simple imitation (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). Greenhalgh et al systematically reviews and discusses the question of how innovations in health service delivery and organizations can be spread and sustained (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). This work offers a model and method for evaluating health services policy and management, which the authors recommend should be tested in a variety of environments to potentially link the determinants of diffusion (e.g., physician and physician practice characteristics) to innovations in health services delivery and organization (e.g., EHRs). One test of the model was performed on a case study for the United Kingdom's electronic patient record, which the authors analyze. The article also exclaims the wide gap between how often Rogers' work is cited in adoption literature and how rarely it is applied in empirically-based research (Greenhalgh, Robert, Macfarlane, Bate, & Kyriakidou, 2004). Much can be gained by tuning policy and programmatic efforts to support EHR adoption to stages and preferences of adoption (Boston University School of Public Health, 2013). This theory has certain limitations, such as not taking available resources in an environment into consideration, which is a factor in health care with varying levels of support infrastructure available to practices implementing EHRs (Boston University School of Public Health, 2013).

Studies applying Rogers' Diffusion Theory can be found in the areas of: nursing, including a qualitative study which concluded Rogers' model can be accurately used to describe nurses behavior while in the process of adopting workplace innovations and a study regarding sustainability of bedside care innovations (Lee, 2004) (Yee, 2010); and long-term care, including

a study in which Rogers' theory of Diffusion of innovation was described as an effective model for improving care to patients in nursing homes and improving performance in healthcare organizations (Kovach, Morgan, Noonan, & Brondino, 2008).

Useful insights into the differences between early adopters (current EHR users) and later adopters (current EHR non-users) point out fundamental differences between these two groups – differences which make it difficult for new technologies to advance from the Innovator and Early Adopter Phases into the mainstream Early Majority and later adopter phases (Loomis, Ries, Saywell, & Thakker, 2002). This challenging transition is called a chasm, since it is a point of failure for many innovations (Boston University School of Public Health, 2013). This chasm points out the need for research into the differences in predictors of EHR adoption between groups on both sides of that adoption chasm and provides a segue into the last section of the Literature Review, *Barriers and predictors of EHR adoption*.

#### *Barriers and predictors of EHR adoption*

Given low EHR adoption rates in physician practices as described above, what factors serve as barriers or predictors of such adoption? The most commonly cited barriers are financial (such as capital costs), time requirements, not finding an EHR system that meets the physician practices' needs, uncertain or negative return on investment and concern that an EHR software product would become obsolete, or concerns that the vendor would be transient and outdated (DesRoches C. , et al., 2008) (Mattocks, et al., 2007). Other barriers cited include lack of user acceptance and issues surrounding leadership and organizational change (Morton, 2009). Other barriers or concerns identified in the literature include: the time needed to practice medicine with an EHR (despite time-motion studies suggesting that while the initial period of time slows productivity,



there might be a slight improvement in time efficiency once the adjustment to the new EHR takes place, and other research showing that EHRs neither increase or decrease time necessary for nurses to perform their documentation (Yee, 2010)); system maintenance; difficulty choosing among the many EHR vendors in today's marketplace; and concern the chosen vendor might go out of business and leave physicians unsupported and without their practice and patient data (DesRoches C. , et al., 2008). Predictors include physician perceptions of quality of care and provider satisfaction, with a focus on EHR adopters are better able to coordinate care, communicate effectively, and deliver safer care (Davis, Doty, Shea, & Stremikis, 2009). In particular, coordination of patient care within practices is improved with EHR infrastructure; coordination across settings is dependent upon process integration and EHR interoperability, both of which are examples of more advanced capabilities included in later stages of Meaningful Use (O'Malley, Grossman, Cohen, Kemper, & Pham, 2009).

Invoking Rogers' diffusion theory, early or imminent EHR adopters differ from later adopters in certain key ways (Robinson, 2009). Imminent adopters are: more likely not in solo practice; more likely to be in family medicine or obstetrics/gynecology; less concerned about start-up costs and return on investment; and generally less concerned about productivity and technology issues (Menachemi N. , 2006). In spite of barriers noted, additional research reports that EHR adoption and market saturation will occur, albeit more slowly than called for by the government's stimulus efforts, according to Rogers' predicted S-shaped diffusion curve, by 2024 (Ford, Menachemi, & Phillips, 2006).

### *Gaps in Literature*

While the number of studies about EHR adoption in physician offices is growing, most only provide statistics on adoption rates. To date, literature beyond adoption rates is lacking regarding specifics associated with EHR adoption in primary care, in particular, and in all physician practice settings. While low rates of adoption in physician practices persist (Bates, 2005) (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015), work is underway to identify what would bring a sense of greater value or return on investment to physicians in adopting EHRs (AHRQ Project Seeks to Cure What Ails Electronic Health Records, 2010). Of studies covering these topics, few studies other than descriptive surveys include large, national samples of physician practices and generalizable predictors to adoption other than cost; many studies are descriptive studies of single practices or practices attached to hospitals that also have EHR systems (Reed & Grossman, 2004).

Research that identifies practice characteristics that have an independent effect on adoption beyond physician characteristics in mainstream medicine remains to be conducted so that policy and management recommendations can apply to the variety of types of practices that comprise physician practices throughout the U.S. Illustrating this variety, about one-half of all physicians practice in primary care specialties, about 28.6% of physicians are in medical specialties, and about 21.5% are in surgical specialties. Since 2001–2002, the proportion of physicians in medical specialties increased by 22%, whereas the proportion in surgical specialties decreased by 18%. Specialties with the most physicians included general and family practice (18.5%), internal medicine (14.3%), pediatrics (10.1%), and obstetrics and gynecology (7.7%) (Hing, Burt, & Woodwell, 2007).

Until the government's HITECH Act stimulus of 2009, most of the attention regarding EHR adoption had been paid to hospital EHR implementations because large, noteworthy implementations occurred there historically (Goldzweig, Towfigh, Maglione, & Shekelle, 2009). Hospitals generally have more capital, more technical support, greater excess capacity, more staff available to promote research in those organizations, and vendor revenue opportunities are greater there so marketing is heavier to hospitals. Less penetration of physician practices with EHR implementations has taken place historically because market is new and not attempted yet by most small practices. Primary medical care and clinical care have been especially difficult to study, because the rate of EHR implementations is lowest in that segment (DesRoches C. , et al., 2008). Studies recommend further research on practice-level barriers to and predictors of EHR adoption (Grant R. , Campbell, Gruen, Ferris, & Blumenthal, 2006). The literature also speaks to the differences between early adopters' and others' identifying predictors, recommending research differentiating between these two categories (Menachemi N. , 2006) (Robinson, 2009).

# Adoption of Electronic Health Records

by Physicians for Use in Their Practices

## Chapter Three

Measuring Electronic Health Record (EHR) Adoption:

Development of the Dependent Variable

### **Introduction**

In today's movement to automate health records, systems, and processes, U.S. health care delivery organizations, provider practices, payers and inter-organizational consortia are aggressively acquiring and implementing health information technology (HIT), with a focus on electronic health records (EHRs). While this movement's roots lie in a more gradual evolution that began in the 1960s in development of administrative computer systems in many hospitals, clinics and physician practices, it has gained significant traction in the past ten years. More recent focus has turned to implementation and adoption of EHRs in these same types of settings (Blumenthal D. M., 2009). Expansion of HIT use in health care has been fueled by the Institutes of Medicine (IOM) reports "To Err is Human" (1999) and "Crossing the Quality Chasm" (2001);

these studies reported dismal outcomes in U.S. quality of care, efficiency, and rates of medical errors and recommended extensive use of HIT to help address these issues.

Adoption rates of robust HIT architectures, especially EHRs, have been surprisingly and stubbornly low, especially in the physician practice setting for small practices, i.e., 1-10 physician groups (Institute of Medicine, 1991) (Committee on Quality of Health Care in America Insitute of Medicine, 1999) (Committee on Quality of Health Care in America - Institute of Medicine, 2001) (Brailer, 2005) (Middleton, Hammond, Brennan, & Cooper, 2005) (DesRoches C. , et al., 2008) (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015) (Rao, DesRoches, Donelan, Campbell, Miralles, & Jha, Electronic health records in small physician practices: availability, use, and perceived benefits, 2011) At the same time, the literature on this topic is inadequate with limited information related to rates of adoption, barriers, or facilitators (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

In the hopes of informing ways to help productive EHR adoption take place, research is needed to understand its characteristics, objectives, barriers, keys to success, nuances, and effects on quality and cost (Jha, et al., 2003) (Robert Wood Johnson Foundation, 2008) (Menachemi N. , 2006) (Grant R. , Campbell, Gruen, Ferris, & Blumenthal, 2006) (Jha A. K., et al., 2009) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

Such research findings and recommendations for keys to safe care and successful HIT implementation are actively being sought from numerous perspectives: from physicians struggling to adopt an EHR in their one-to-ten physician practice, to large-scale health system EHR implementations; to nationwide initiatives intended to build out HIT infrastructure for Medicare and Medicaid cost-effectiveness programs such as Accountable Care Organizations

(ACOs), medical homes, and chronic care management; as well as universities and other organizations conducting research on patient safety, quality, and innovation (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015).

**Measuring EHR Adoption:** Sound dependent variable development for EHR research based on insight into the multiplicity of dimensions of EHRs and accuracy in defining research questions appropriate to the scope of the data, will result in improved research findings to more precisely inform EHR adoption and begin to ameliorate today's wild differences in research results regarding EHR adoption.

With several variations, but no one standard definition for the content or capabilities of an EHR, and no consistent scope of implementation within organizations, a meaningful answer to the questions such as "Does your practice have an EHR?" and "Do you use an EHR to care for patients?" eludes us (Ashish K. Jha, 2010) (Institute of Medicine, 2003) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012). Measuring EHR adoption requires more detail about the specifics of what has been implemented and is in use. What *functionality* must be present to constitute the existence of an EHR? Further, what constitutes EHR *adoption*? Who is using what types of computer functionality; to accomplish implementation and achieve adoption of an EHR; and then, what is the appropriate way to measure such adoption? In summary, the scope of what is being measured varies significantly, but the label of EHR is being applied to all those variations in scope of HIT or EHR capability. Thus, the comparability of results from one EHR study to another is inappropriate, but done on a regular basis. It is essential to develop a dependent variable with enough specificity to warrant its name and role in a study of this nature.

In this chapter, seven data elements regarding use of specific EHR-related IT functionalities among physician respondents of a national survey are used to develop the dependent variable for the other analyses presented in this dissertation in Chapters 4 and 5.

### **Why does this problem in measurement of EHR adoption matter?**

EHR-related studies conducted to date report mostly on rates of adoption, barriers to adoption, and other general results. These studies are based on data from multiple and disparate types of data sources and surveys, scopes of organizational settings, and definitions of systems referred to as electronic medical records or EHRs, making comparisons across studies difficult if not impossible (Grant R. , Campbell, Gruen, Ferris, & Blumenthal, 2006). (Hing & Hsiou, Electronic Health Record Use by Office-based Physicians and their Practices: United States, 2007). (Robert Wood Johnson Foundation; George Washington University Medical Center; Institute for Health Policy, 2006) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012)

The dependent variable must be developed according to the context of the study, as well as the data used for a study. In developing the dependent variable, techniques such as Factor analysis, Cronbach's alpha, and Guttman scaling can be used to determine whether or not the data available for creating the dependent variable scales or not. Factor analysis can be used to uncover an underlying structure of the variables, Cronbach's alpha to determine the internal consistency or average correlation of items in a survey instrument to gauge its reliability, and Guttman scaling to help determine whether a one-dimensional continuum can be created to measure a response to a survey (Santos, 1999) (Trochim, 2008). Additionally, a study's generalizability relies on careful attention to proper definition of the denominator, or population to which results

may be properly applied. Exploratory factor analysis, Cronbach's alpha, and Guttman scaling are all applied in this analysis to determine the structure of the dependent variable. Research using precise measures and setting samples that get be generalized to populations appropriately will produce the generalizable results needed to understand and untangle the complexities of EHR systems and their adoption. Specific EHR/IT functionalities that are being actively used should be measured rather than answers to general questions such as "does your practice have an EHR?" or "does your EHR have CPOE capabilities?" Jha and DesRoches have changed the landscape with their watershed "basic" and "comprehensive" EHR functionality definitions for hospitals. (Jha A. K., DesRoches, Kravolec, & Joshi, 2010) Meaningful Use provides specific functionality criteria to focus on by those organizations participating in the program. However, at this time, only 44% of physician practices are participating in Stage 2 Meaningful Use and an estimated 22% of providers plan to opt out of the program. (HITC Staff, 2015) (Pennic, 2014) Thus current research is characterized by lack of consistency in measurement of EHR adoption, due to and varying scopes and definitions of these systems. This has resulted in limited generalizability of results due to under-development of the measurement construct, i.e., the dependent variable, *adoption*, and inappropriate generalization of research results beyond the scope supported by the data (Robert Wood Johnson Foundation; George Washington University Medical Center; Institute for Health Policy, 2006) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

Improved research—dependent upon improved precision in measurement of EHR adoption by better definition—will produce research results that: 1) are able to be more appropriately generalized to the population(s) of those providers and organizations adopting EHR capabilities similar to those being studied; 2) more accurately and reliably evaluate the quantity and quality



of EHR implementations (adoption); 3) more precisely relate specific EHR functionality to quality and cost outcomes; and 4) uncover with greater insight, the reasons and recommendations for ways to use EHR systems.

### **EHR Measurement Issues in Current Literature**

In current literature, published research measures EHRs in varying ways:

- 1) Not at all—the term EHR is used in the body of the paper with no definition attached;
- 2) Most published literature refers to EMRs (electronic medical records) as the same as EHRs—the term EMR is used interchangeably with the term EHR, whether one or a thousand providers use it (Ashish K. Jha, 2010);
- 3) More logical approaches such as a singular study setting thresholds for “basic” and “comprehensive” EHR functionality (Jha A. K., et al., 2009);
- 4) Adoption measures come from self-reported data, with a strong financial and cultural incentive to say, “yes” (Networks, 2012) (Blumenthal D. M., 2009);
- 5) Meaningful Use criteria for Phase One or Phase Two incentive payments form the basis of the definition for an EHR, with only partial participation in use of these criteria;
- 6) Papers written to publicize organizational objectives or advocate an organization as a potential recipient for an industry award, such as Hospital and Health Networks “Most Wired Award,” are sometimes politically influenced and subjective, lacking EHR specifics. In these cases, the report is often prepared by internal staff/IT professionals reporting to CIOs and CMIOs, whose jobs are based on meeting those organizational objectives (Networks, 2012);

- 7) Articles written by EHR software vendor representatives wanting to display successes of their product offerings with general descriptions of EHRs at a high level, lacking specifics regarding EHR functionality, which are further compromised in their trueness by restrictive contracts with EHR software vendors that prohibit sharing negative experiences or problems associated with the software; (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012)
- 8) Lack of use of common definitions of basic and comprehensive functionality, EHR adoption, or other definitional standards (Jha A. K., et al., 2009);
- 9) Lack of studies investigating functionality detail or context as it relates to specific processes and outcomes (Goldzweig, Towfigh, Maglione, & Shekelle, 2009); and
- 10) Studies that do not measure percentage of penetration of the EHR into departments of an organization or practice.

**To understand EHR Adoption, the definition of EHR must be clear for accurate**

**measurement:** First, accurate measurement of EHR adoption is essential to conducting good research. Without a well-developed and appropriate dependent variable, studies will be flawed, due to threats to validity, endogeneity and other problems. This is especially serious since EHRs are used to automate processes of clinical care, so actions implemented based on inaccurate findings pose a threat to patient safety. Second, the need and goal of EHR adoption research goes well beyond uncovering how many EHRs are implemented, who uses them, and what characteristics accompany adoption. The deeper goal of EHR research is to inform the use and effect of EHR functionalities, how those functionalities interact in combinations, how functionalities interact with processes, the effect of these combinations on outcomes, how

providers engage patients in management of their care, and how functionality and processes can be influenced, supported, and enabled to improve outcomes. Third, the goal of EHR adoption research is to identify the reasons behind the unintended consequences EHR adoption is currently creating—a concerning situation given the massive investments being made in EHR implementations across the U.S. Good research is needed to enable these new systems to take the health care system in the intended positive direction (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

**Definitions of systems and functionality for clinical processes are ambiguous compared to those for financial and administrative processes:** Generally accepted definitions for EHR scope, functionality, and capabilities required for specific clinical processes are just being introduced compared to the long-established, standardized, definitions for accounting or business systems in health care. In administrative functions, for example, there are published standards of practice and professionalism based on Generally Accepted Accounting Principles (GAAP) rules used throughout the financial management world, including healthcare finance (Federal Accounting Standards Advisory Board (FASAB), 2011). These standard metrics and measures for financial and administrative processes are widely used for certification, accreditation, audits, reporting, and research. The clinical world differs—there are few commonly accepted standards and ways of doing things. This phenomenon contributes variability and randomness to measurement of clinical functions—measurement also depending on the opportunity a researcher might have to gain access to data of some sort or another regarding EHR adoption.

As a result, definition of the dependent variable for research in this area is inconsistent among organizations, research studies, and the published literature. This situation presents a serious impediment to progress in EHR adoption and improvement of the use of these systems in clinical

settings. An indicator of widely inconsistent measures of EHR adoption is that research results vary widely between studies measuring similar elements of EHR adoption (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012). For example, in published results regarding adoption of an important element of EHRs, computerized physician order entry or CPOE, adoption results reported in the literature range from 5% to 24% (Robert Wood Johnson Foundation; George Washington University Medical Center; Institute for Health Policy, 2006); Jha et al found adoption levels in hospitals ranging from 10.9% to 1.5% percent, depending on whether the EHR met the definition of “basic” or “comprehensive” functionality, respectively, thus highlighting the critical importance of the definition of the details and scope of an EHR when measuring adoption (Jha A. K., et al., 2009). DesRoches et al found in a 2013 survey of physicians that 43.5% reported having a basic EHR, but only 9.8% achieved Meaningful Use criteria (DesRoches, Audet, Painter, & Donelan, 2013).

When EHR studies are examined in more depth, for instance in the CPOE example, it can be seen that the way adoption of CPOE is measured is at the root of the wide variation in results. To measure the use of CPOE in an organization, it must be examined from a number of dimensions. For instance, what does it mean to say that CPOE exists in an organization? Does it mean that CPOE functionality is available to use on that organization’s computer system and that physicians can choose to use? Or does it mean that 100% of physicians write 100% of their orders using the EHR CPOE capability—or something in between? An organization’s policies and practices drive what it means to have “adopted CPOE.” In-depth work remains to be accomplished to develop reliable, precise, and widely accepted methods of measurement of EHRs and their adoption. This phenomenon is largely ignored in today’s EHR adoption research, as data for researchers to use for EHR adoption research is not plentiful, while demand for such

research is high. So researchers use what data is available, but because EHR adoption is not well understood, these flaws persist and are not adequately weeded out through the study development or peer review processes. Few studies have attempted to address this definitional chasm (Jha A. K., et al., 2009) (Kern, Wilcox, Shapiro, Shopeshwarkar, & Kaushal, 2012) (Include the 7 phases by HIMSS) (DesRoches, Audet, Painter , & Donelan, 2013).

Additionally, the issues described above occur in the context of intra-organizational EHR adoption. What about inter-organizational usage? When considering health information exchange (HIE) as a key EHR capability now that HIE is part of Meaningful Use and needed for Accountable Care Organizations, medical homes, and chronic care management to be accomplished, this area must be dissected to determine appropriate metrics for measurement of EHR use of HIE. For instance, do you count by numbers of types of interaction or do you count by having the capability activated? What is the locus of control in this case? Many interesting and important questions exist in this arena, and should be studied in subsequent research.

**Knowledge gap in EHR Adoption:** What we know (and don't yet know) about EHR adoption from the published literature is resulting in low EHR adoption rates in the U.S., especially for small and rural physician practices and those providing the safety net of care for those with limited access to care. Additionally, this knowledge gap is yielding poor results in connecting EHR use to improvements in quality and efficiency of care.

Improved measures of EHR adoption are essential to:

1. produce research results that are generalized to the proper populations;
2. better reveal the systemic influencers of EHR adoption, in the context of historic and recent levels of investment in HIT in the U.S. (how much);

3. allow researchers to begin to stitch together the relationship between use of specific types of EHR functionality and processes;
4. provide evidence regarding the net effects of combining EHR functionality and processes on improvements or degradations in quality, access, and cost performance; and
5. produce research that allows us to gain insights into EHR adoption among those subgroups with the lowest adoption rates, such as in smaller physician practices, where the majority (60%) of health care in the U.S. is delivered (Robert Wood Johnson Foundation; George Washington University Medical Center; Institute for Health Policy, 2006) (Jha, et al., 2006) (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015).

In EHR adoption study design, it is important to:

- 1) take EHR scope of use differences into account in developing the dependent variable of EHR adoption;
- 2) generalize to a population carefully and appropriately, based on 1; and
- 3) define accurate population/sample for denominator.

### **Study Aim: develop dependent variable**

The aim of this chapter's analysis is to develop the dependent variable "Total IT Adoption" to measure EHR adoption by physicians in the studies in this dissertation.

In developing the dependent variable, factor analysis, Cronbach's alpha and Guttman are used to determine whether the data available for the dependent variable scales. Study results will be generalized to the universe of U.S. physician practices, and in the case of Chapter 5, to physicians practicing in office-based settings.

Chapters 5 and 6 of this dissertation, report on the analyses of data from the Community Tracking Study—Physician Surveys 2000/1 and 2004/5 as a means of providing an EHR adoption baseline, examining EHR adoption by physicians during the pre-ARRA era when financial incentives were not available. The first step toward conducting these analyses was to develop an appropriate dependent variable, “*EHR Adoption*,” using these data. The process by which the dependent variable development was accomplished follows.

## **Methods**

### **Developing the dependent variable: *EHR Adoption***

This section describes the methods used in developing the dependent variable “Total IT Adoption” for Chapter 4: “Adoption of EHRs by Physicians for Use in their Practices” and Chapter 5: “Panel Analysis of Physician Adoption of Electronic Health Record System (EHR) Capabilities” of this dissertation.

The first question in developing the dependent variable is:

What data elements are available to develop dependent variable? In this case, there are seven (7) survey questions asking whether or not the respondent physician’s practice uses each of the seven (7) types of EHR functionality.

An early question in developing the dependent variable for EHR Adoption is, “Do these seven data elements scale”? In this case, are the EHR functionalities included in this survey of physicians typically implemented in a certain order or in certain combinations? Are these EHR functionalities adopted in categories of functions, with shared factors, grouped together? If so,

what is the order, set of common factors, or groupings of functionality? If there is no typical order or grouping, then they may be just counted and an “IT Adoption Score” applied.

### **Statistical Analysis:**

The analysis for creating the dependent variable for this study and data set evaluated the seven EHR-related data elements from the CTS-Physician Surveys using exploratory factor analysis, Cronbach’s alpha, and Guttman analyses. These tests were performed to evaluate whether there were groupings or natural categories of EHR functionality adoption occurring within the data. If natural categories did exist, a scale would emerge and be identified in terms of the order of types of functionality adopted and potential groupings then of the seven individual EHR capabilities into a few types of categories. If no scaling occurred, then a continuous score yielding the total number of EHR functions adopted by the physicians for use in their practices, regardless of the type of functionality, could be developed and used as the dependent variable measuring EHR adoption for the analyses.

The seven (7) “computer-use” HIT variables available in the data are related to or support the use of an EHR. These Yes/No HIT- and EHR-related questions in the surveys are:

1. **Computers used for treatment guidelines** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information about treatment alternatives or recommended guidelines?
2. **Computers used for formularies** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information on formularies?



3. **Computers used for preventive service reminders** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to generate reminders for you about preventive services?
4. **Computers used for patient notes or medication lists** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to access patient notes, medication lists, or problem lists?
5. **Computers used for writing prescriptions** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to write prescriptions?
6. **Computers used for exchanging data with other physicians** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used for clinical data and image exchanges with other physicians?
7. **Computers used for e-mail with patients** [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to communicate about clinical issues with patients by e-mail?

Exploratory Factor, Cronbach's Alpha, and Guttman analyses were conducted to determine whether there exists some pattern of relationship between these seven "computer-use" variables regarding the use of these EHR functionalities: factor analysis to examine whether grouping can be done based on common factors into categories such as patient care, guidelines, and prevention, or other like types of functionality based on an underlying relationship; Cronbach's alpha to test the internal consistency or correlations between the variables and see if they form a

scale; and Guttman test to see if the items form a scale based on a factor that differentiates the variables from one another (Darlington, 1991) (Choudrhury, 2010).

### **Results:**

Exploratory factor, Cronbach, and potential Guttman analyses were used to see if a sequence or sub-scale of adoption existed across the seven EHR functionalities. More specifically, factor analysis was used to examine whether sub-scales appeared to exist in which the seven uses could be organized into categories such as Clinical Communication, Mechanics of the Practice, or Clinical Care.

Based upon the analysis conducted there was no evidence of sub-scale structure, or that adoption was sequenced. The exploratory factor analysis recovered only one factor, and did not disclose any subscale structure.

Exploratory Factor Analysis (Tables 3-1, 3-2):

The factor analysis results show that each factor has about the same weight and uniqueness. The percentages are about even, and there is no structure to the adoption of EHR functionality. The likelihood of any EHR functionality is about equal. The factor analysis shows there is only one factor, so there is no subscale here.

Cronbach's alpha (Table 3-3): Cronbach's alpha was used to test internal consistency of the "Computer Use" items to see if they formed a scale. The data were examined with a sub-routine to examine whether the adoption followed a Guttman scale in which some capabilities always preceded others, and this was not the case. The Cronbach's alpha we found the overall level of scalability was modest level of evidence of a scale for these items (CA = of 0.7). Logical

subscales were tested based upon a functional analysis (subscales paragraph) and the Cronbach's alpha estimated for these three sub-scales ranged between 0.48-0.69, all lower than the level lower usually considered evidence of a scale (typically 0.8).

Sub-scales tested: Based on the relationship between types of functions contained in the seven computer-related questions, three sub-scales were created to test whether those logical groupings scaled. The sub-scale groupings tested included:

Sub-scale 1: Clinical Communications - "Computers used for treatment guidelines", "Computers used for exchanging data with other physicians", and "Computers used for e-mail with patients email."

Sub-scale 2: Mechanics of the Practice - "Computers used for formularies, "Computers used for preventive service reminders", "Computers used for patient notes or medication lists", "Computers used for writing prescriptions", "Computers used for exchanging data with other physicians", and "Computers used for e-mail with patients."

Sub-scale 3: Clinical Care - "Computers used for patient notes or medication lists," "Computers used for writing prescriptions," and "Computers used for exchanging data with other physicians."

The variables applying Cronbach's Alpha showed no significant correlation between the seven computer-use variables in total, or in three groupings: Subscale 1 – Clinical communication; Subscale 2: Mechanics of the Practice; and Subscale 3: Clinical Care, with the exception of Subscale 3: Clinical Care for the 2004/5 dataset.

As the maturity of the implementation increases, these clinical care EHR functions become more widely used, and will tend to be used together, indicating an increased depth of EHR adoption among those practices. In other words, if the practice is capable of adopting one of these more advanced functions to automate a clinical care process, the practice may be able to—and desirous of—adopting the other two more advanced clinical care functions as well. These less-frequently adopted functions tend to be adopted together.

Results of the Cronbach's Alpha test of these three sub-scales show no significant reliability between items, and provide evidence that on average that the subscales do not hold together well as subscales, among the physicians in these survey samples, using all the questions, and using the sub-scales of related capabilities.

Tetrachoric (Tables 3-4a, 3-4b): The tetrachoric correlation matrix results for 2000-2001 and 2004-2005 indicate some of the EHR adoption or "Computer-use" variables are more commonly adopted than others, but there is no structure to the adoption. There is no evidence of a high correlation between these computer-use variables and no structured sequential adoption pattern. Tetrachoric correlations analysis shows that all the correlations are between 0.3 and 0.6 and there is no internal structure indicating a variable is correlated with another.

Therefore, the dependent variable used to measure IT Adoption for this study is a continuous variable (0, 1, 2, 3, 4, 5, 6, 7); it calculates a cumulative score across the seven questions answered by the physicians participating in the surveys. The IT Adoption Score "Total\_it" is the variable name for the dependent variable in this analysis.

Table 3-5: Percentages of installations with each IT variable in combination with least used IT capability: "*Use of the computer to write prescriptions*". This table presents results of cross-

tabulation of use of each of the IT functionalities in combination with the least-used IT capability, “Use of the computer to write prescriptions” to show combinations of the various functionalities and observe possible patterns in adoption – none were evident from this analysis.

**Discussion:**

While it was anticipated that some logical order or groupings would have emerged from the data elements representing the different types of EHR functionality, none such order was evident; this order logically might have reflected increasingly complex or sophisticated EHR-related functionality to be adopted in some systematic fashion in the physician practices. It was also examined whether the seven IT-related functions would group together into those that would have some relationship based on the types of tasks they support: Clinical Communications, Mechanics of the Practice, and Clinical Care-related activities. But the use of functions did not group into these sub-scales.

The analysis indicates that these EHR functions were implemented in no particular order and in various sequences across these practices. So it was determined that the dependent variable is a continuous variable representing the sum of IT functionalities adopted by each respondent, ranging from 0-7, and that the score is a cumulative score of the IT functionalities adopted.

These results also support the notion that each EHR implementation is unique: while each of the physician practices would probably answer “yes” to the overall question, “Does your practice use an EHR?” the content of each implementation varies over this population of physician practices and time period. Thus, any results indicating predisposition to implementation such as physician characteristics or practices characteristics, would be associations unrelated to any predisposed patterns or relationships between the variables, or sequence or groupings of EHR functionalities.

This finding, combined with the low adoption rates seen in physician practices during this time period, also suggests that a consistent EHR-implementation methodology is lacking among these practices. Such a systematic approach might be helpful in improving adoption rates and the uptake of higher rates of EHR functionality.

### **Discussion of Implications for development of Dependent Variable for EHR Adoption**

#### **Research:**

The dependent variable for IT Adoption research varies widely between studies in this area. Certain frameworks specifying EHR functionality have been established since the time of these surveys, such as “basic” and “comprehensive” EHR functionality as well as Meaningful Use criteria. So to provide a pre-ARRA dependent variable for EHR adoption, seven “Computer-use” variables were used to measure EHR adoption in its early stage. This early stage EHR adoption analysis can provide a baseline against which subsequent research can be based.

Since the time of these surveys we remain at a point where a disconnect between EHR adoption and research clouds the relationship between EHR usage and patient safety – as a result, little visibility exists into unintended consequences of EHR adoption. For all the promise that EHR systems hold for improving quality, access, efficiency, and patient safety, growing evidence shows they can also create quality, process, and patient safety issues, resulting in untoward, unpredictable outcomes. (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

Thus it is imperative that improved research on EHR adoption is conducted, so that as the massive wave of EHR installations and investment is occurring, we can learn and do better. To prevent a furtherance of a potentially new form of electronic iatrogenesis (Merriam-Webster

Dictionary, 2012) we must develop the necessary insights into proper EHR implementation and management, so that current investments in EHR adoption bring not only an increase in rates of adoption, but the much-hoped for improvements in clinical quality and effectiveness.

As the government pours billions of dollars into the stimulus of EHR adoption, we are compelled to learn from new knowledge produced by excellent, generalizable research published in the literature, and not from hearsay or vendor propaganda. This careful, accurate research will show us how to safely adopt EHRs for improved safety, efficiency, and quality of patient care. This is certainly what the government foresees in the HITECH Act, through the development of Meaningful Use criteria and other parameters. This is consistent with EHR-driven improvements as envisioned by every organization attempting to implement an EHR and by the Institute of Medicine in its recommendations for more extensive use of health IT to improve quality of U.S. health care as identified in “To Err Is Human” (Committee on Quality of Health Care in America Insitute of Medicine, 1999).

By first understanding the pitfalls in current measurement methods, as well as apply the good EHR measurement work of Jha, DesRoches, and others, researchers can define appropriate measurement methods to apply in EHR adoption research.

**Limitations:** Using this sample, the primary issue is that single physicians are answering the survey for a practice from his/her perspective, so it is not known whether the yes/no answers from the physicians for a practice are representative of the full depth and breadth of EHR functionality for that practice or simply for these physicians’ usage of the EHR functionality.

Additionally, there are only seven questions related to use of the computer in the physician practices that are used to represent EHR adoption; while these are a decent representation of

types of EHR functionality used in physician practices especially for this time period, there are probably uses of an EHR in some practices than are represented by these seven questions. These other EHR functions may be important differentiators in physician and practice characteristics that were not included in the seven questions. The scope of additional EHR functionality used in these settings beyond the questions asked might vary considerably, so there could be other factors at work that are not discernable using this particular data set. This study is reliant on the random sampling methodology to result in a representative sample of the population of all physicians. So while the contexts from which the data are gathered vary significantly, validity of the measure of EHR adoption and generalizability of results to overall populations of physician practices is as good as the sampling and survey methodology. It is difficult to know if a good sampling and survey methodology will account for variations in the breadth and depth of EHR usage and scope among the physician practice settings at this point in the evolution of EHR adoption research.

**Further research questions regarding the measurement of EHR Adoption:**

Further research should be performed using similar analyses (Exploratory Factor, Cronbach's alpha, Guttman analyses) to develop the dependent variables for analyses using datasets from subsequent rounds of the CTS survey (2008 and 2012). The CTS survey methodology for subsequent rounds was changed however, and additional "Computer Use" questions were added to the later surveys. So while these results could not be directly compared to the later rounds, certain differences or similarities would be important to understand. Additional insights into order, grouping, or scaling of functionality would add to the body of knowledge regarding EHR adoption and its evolution.



Post-ARRA research should be done using this study as baseline, which would give perspective to changes in the maturity of EHR adoption by physicians for use in their practices in the context of environmental factors as well. This could give a sense as to the effect of time, policy, and other key variables that have changed since the early adopter phase of EHR adoption.

Researchers could also test for “basic” vs. “comprehensive” functionality, and relate these “Computer Use” variables to those specific functionalities. Functionality “markers” could potentially be developed to show whether EHR use is “basic,” or “comprehensive.” “Basic” vs. “comprehensive” functionality also could be examined by functionality capabilities, e.g., electronic prescribing, or clinical documentation, or CPOE, to examine the relationship of EHR functionalities to quality and cost outcomes.

The main issue is that it will be helpful to get this level of clarity on specific and accurate measurement of EHRs *before* we will be able to tie EHR functionality to processes, EHR-enabled processes to integration, and integration to outcomes in any meaningful way. Additional work could be done comparing the same datasets analyzed with different approaches to developing the dependent variable to assess any differences in results.

These pre-ARRA results serve as a baseline against which post-ARRA results for similar adoption analyses can be performed. Also, an interesting area of investigation would be to compare the differences in physician and practice characteristics between these results, which are for the “Innovators” (pre-ARRA) to “Early Adopters” and “Early Majority Adopters” (post-ARRA) on the Rogers’ Diffusion of Disruptive Innovation Adoption Curve.

## **Conclusion**

Measuring Electronic Health Record (EHR) adoption depends on thoughtful development of the dependent variable against which the association or influence of various independent variables can be estimated. With highly varying types of data reflecting use of EHR systems as the norm, comparability of EHR adoption results is limited, since results will vary significantly depending on what amount and type of usage data are accessible.

This chapter describes the development of the dependent variable using seven “Use of Computer” EHR-related data elements from the CTS Physician Survey Rounds 3 and 4. Exploratory Factor, Cronbach’s alpha, tetrachoric, and Guttman analyses identified no particular orders, groupings, scale or sub-scales within the seven “Computer-use” variables. Thus the dependent variable for EHR adoption for the analyses contained in Chapters 4 and 5 of this dissertation is a continuous variable with scores form 0 – 7.

As these surveys were conducted during the pre-ARRA timeframe, this dependent variable provides a useful baseline for post-ARRA comparison and evaluation, as well as perspective for post-ARRA analysis between “early adopters” according to Rogers’ Diffusion of Disruptive Innovation Adoption Curve.

## Tables

**Table 3-1: Factor loadings (pattern matrix) and unique variance: 7 computer-use variables**

2000–2001 Dataset			2004–2005 Dataset		
Factor	Eigenvalue	Cumulative	Eigenvalue	Cumulative	
Factor 1	2.52765	0.3611	2.59494	0.3707	
Factor 2	0.96312	0.4987	0.95669	0.5074	
Factor 3	0.82869	0.6171	0.85018	0.6288	
Factor 4	0.78964	0.7299	0.82833	0.7472	
Factor 5	0.71966	0.8327	0.67067	0.8430	
Factor 6	0.61209	0.9201	0.60235	0.9290	
Factor 7	0.55915	1.0000	0.49684	1.0000	
Factor Loadings	2000-2001 Dataset		2004–2005 Dataset		
Variable	Factor 1	Uniqueness	Factor 1	Uniqueness	
IT Item 1	0.5834	0.6596	0.5499	0.6976	
IT Item 2	0.6724	0.5479	0.6318	0.6008	
IT Item 3	0.5200	0.7296	0.5355	0.7132	
IT Item 4	0.6873	0.5276	0.7155	0.4880	
IT Item 5	0.5568	0.6900	0.6184	0.6176	
IT Item 6	0.6562	0.5694	0.6767	0.5421	
IT Item 7	0.5018	0.7482	0.5043	0.7457	

**Table 3-2: Factor result**

<b>Factor</b>	<b>Variance</b>	<b>Difference</b>	<b>Proportion</b>	<b>Cumulative</b>
Factor1	2.52765	.	0.3611	0.3611
LR Test: independent vs. saturated: $\chi^2(21) = 1.2e+04$ Prob> $\chi^2 = 0.0000$				

<b>Table 3-3: Cronbach's Alpha Reliability Statistics</b>			
<b>Year</b>	<b>Scale Reliability Coefficient</b>	<b>Average Interitem Coefficient</b>	<b>Number of Items</b>
2000-2001 All	0.7011	.049085	7
2000-2001 Sub-scale 1*	0.5212	.0572296	3
2000-2001 Sub-scale 2**	0.6712	.0473625	6
2000-2001 Sub-scale 3***	0.5752	.0586797	3
2004-2005 All	0.6929	.0598618	7
2004-2005 Sub-scale 1*	0.4895	.0530623	3
2004-2005 Sub-scale 2**	0.6929	.0598618	6
2004-2005 Sub-scale 3***	0.6587	.0882847	3

\*Sub-scale 1: Clinical communication (1, 6, 7)

\*\*Sub-scale 2: Mechanics of the practice (2, 3, 4, 5, 6, 7)

\*\*\*Sub-scale 3: Clinical care (4, 5, 6)

**Table 3-4a: Matrix of tetrachoric correlations among IT computer-use variables**

**2000–2001**

**IT Computer-use**

<b>Variables</b>	it_item1	it_item2	it_item3	it_item4	it_item5	it_item6	it_item7*
it_item1	1.0000						
it_item2	0.5620	1.0000					
it_item3	0.3484	0.3997	1.0000				
it_item4	0.3585	0.5195	0.4184	1.0000			
it_item5	0.3048	0.5283	0.4666	0.6277	1.0000		
it_item6	0.4649	0.4799	0.3168	0.5911	0.4088	1.0000	
it_item7	0.4198	0.3685	0.2668	0.3875	0.2894	0.4586	1.0000

\*Item 1 = treatment guidelines; Item 2 = formulary guidelines; Item 3 = preventive service reminders; Item 4 = Patient notes or medication lists; Item 5 = writing prescriptions; Item 6 = exchanging data with other physicians; Item 7 = e-mail with patients

**Table 3-4b: Matrix of tetrachoric correlations among IT computer-use variables 2004–2005**

**IT computer-use variables** | it\_item1 it\_item2 it\_item3 it\_item4 it\_item5 it\_item6 it\_item7\*

it_item1	1.0000						
it_item2	0.5675	1.0000					
it_item3	0.3424	0.4105	1.0000				
it_item4	0.3826	0.4535	0.3924	1.0000			
it_item5	0.2517	0.4268	0.4653	0.7017	1.0000		
it_item6	0.4404	0.4345	0.3361	0.6649	0.4894	1.0000	
it_item7	0.3656	0.3608	0.3287	0.3870	0.3504	0.4201	1.0000

\*Item 1 = treatment guidelines; Item 2 = formulary guidelines; Item 3 = preventive service reminders; Item 4 = Patient notes or medication lists; Item 5 = writing prescriptions; Item 6 = exchanging data with other physicians; Item 7 = e-mail with patients

<b>Table 3-5: Percentages of installations with each IT variable in combination with least used IT capability: “Use of the computer to write prescriptions”</b>				
	<b>2000–2001</b>		<b>2004–2005</b>	
<b>Other Capabilities</b>	ITPRESC Write prescriptions <b>with</b> EHR (11.8% of sample)	ITPRESC Write prescriptions <b>not with</b> EHR (88.2% of sample)	ITPRESC Write prescriptions <b>with</b> EHR (22.95% of sample)	ITPRESC Write prescriptions <b>not with</b> EHR (76.99% of sample)
IT_TRT Treatment guidelines	72.07	49.52	77.51	62.15
IT_Form Formularies	65.75	25.18	68.80	38.90
ITRMNDR Preventive Services Reminders	53.69	20.59	52.75	22.38
ITNOTES Patient notes or med lists	78.11	28.28	87.08	36.90
ITCLIN Exchange data w/ other physicians	66.23	34.81	75.39	41.05
ITCOMM E-mail w/ patients	35.00	17.66	39.70	19.19

# Adoption of Electronic Health Records

## by Physicians for Use in Their Practices

### Chapter Four

#### Changes in Adoption of EHRs by Physicians for

#### Use in Small- and Medium/Large-size Practices during a period of National Policy Intervention

##### **Introduction**

The adoption of electronic health records (EHRs) has captured the attention of health services providers across the nation, especially physicians considering EHRs for their practices, (Bates, 2005) (DesRoches C. , et al., 2008). Despite EHR adoption being a goal for many years (Institute of Medicine, 1991) (Committee on Quality of Health Care in America, Institute of Medicine, 2001), rates of adoption are currently low among providers, estimated at 17% and 10% in physician practices and hospitals, respectively (Blumenthal D. M., 2009) and moving slowly even with Meaningful Use incentives from 11.8% in 2007 to 39.6% in 2012 for physicians meeting criteria of a basic system (Hsiao, Hing, & Ashman, No. 75, 2014). With added emphasis on improving quality and cost performance in health care, the U.S. government has set the



implementation of EHRs as a priority, with direction-setting visions of EHRs for all people in the U.S. by 2014 from both President George W. Bush and President Barack Obama. In this study, we will examine whether the numerous policy, payment incentives, and general environmental conditions occurring during this study time period induced differential changes in EHR adoption by physicians in small and medium/large practices. Small practices have continued to lag behind medium/large practices in adoption of EHR systems, and this study describes the differences in this pooled sample between small and medium/large practices and relationship to physician and practice characteristics associated with those adoption rates over time.

During his administration, George W. Bush signed into law several initiatives stimulating the adoption of electronic health records and health information technology into health care delivery. These included the Medicare Prescription Drug Improvement and Modernization Act (MMA) of 2003, which included important provisions for the development of health information technology including standards for electronic prescribing, an early step in widespread use of electronic health records and requiring establishment of a Commission on Systemic Interoperability to provide a plan for interoperability standards; and, the Executive Order 13335 of April 27, 2004, entitled Incentives for the Use of Health Information Technology and Establishing the Position of the National Health Information Technology Coordinator, and the “President’s Health Information Technology Plan,” calling for a 10-year plan to have health records on-line for all Americans (Thompson & Brailer, 2004) (Bush, 2004) (Orders, 2011) (Bernstein & Broccolo, 2006). These national policy interventions were preceded by other major national initiatives, including the Consolidated Health Informatics (CHI) initiative in 2003 involving Health and Human Services (HHS), the Departments of Defense (DoD), and Veterans Affairs (VA), which declared the adoption of uniform standards for electronic exchange of clinical health information

across all federal health care entities (Thompson & Brailer, 2004). The clarion call of these policy interventions induced physicians and institutional health care providers alike to invest the human and financial capital necessary to undertake the desirable but daunting task of implementing and adopting electronic health records for use in their practices. At the same time, evidence existed of payment incentives averaged \$44,000 per year per provider associated with adoption of EHR systems in small practices (one to two physicians) (Miller, West, Brown, Sim, & Ganchoff, *The Value Of Electronic Health Records In Solo Or Small Group Practices*, 2005). However, such adoption has continually proven elusive for small physician practices vs. their medium/large counterparts and this disparity between small and medium/large practices' EHR adoption is borne out in the literature (DesRoches C. , et al., 2008). This study is motivated by a desire to understand this disparity between small and medium/large physician practices' and whether national policy intervention, payment incentives, and general environmental conditions influence the respective capacities and abilities of these practices to implement EHR health information technology.

Since these early policy interventions and payment incentives targeted at stimulating electronic health record adoption, a growing literature has examined reasons for low EHR adoption rates as well as barriers to and predictors of EHR adoption. Physician practices, especially small ones, are challenged in adopting EHRs, contributing to slow adoption rates overall (Reed & Grossman, 2004). Additionally, Menachemi and Brooks describe low adoption rates among physician practices, especially small practices (Menachemi & Brooks, 2006). In their discussion of factors that may be associated with low rates of EHR adoption, Burke-Bebee and Higgins describe modifiable factors, such as perception of barriers, benefits, and non-modifiable factors, such as practice or physician characteristics (Burke-Bebee, 2008). It is perhaps these perceptions of

barriers that seem insurmountable to individual or small practices with their more limited organizational infrastructural support (e.g., extra support staff, equipment, other IT or “back-office” resources) that results in hesitancy to adopt EHRs within this group. In a smaller practice, any individual factor or barrier may have a more pronounced effect than the same characteristic in a larger practice where such effect would be muted. These factors may be influenced by a policy intervention such as the Bush establishment of the Office of the National Coordinator of Health Information Technology (ONC), calling for widespread establishment of interoperable EHRs within 10 years (Bush, 2004) (Daugherty, 2008). They may also be influenced by payment incentives through increased payments due to more thorough documentation of patient visits using an EHR, resulting in a form of up-coding. In order to examine factors associated with EHR adoption in more depth, and whether these factors in small vs. medium/large practices respond to policy, this study aims to explore EHR adoption by small and medium/large physician practices overall and specifically to examine differences in adoption rates between small and medium/large practices over time. The period between the two rounds of the survey was a period of national policy interventions with the broad, well-publicized intellectual and political energy leading up to the signing of those executive orders, reimbursement incentives, and other changes during the time period of the two rounds of survey data (2000–2001 and 2004–2005). This study examines how large and small practices differed in EHR adoption over this period, allowing inferences to be drawn about the relative ability of between small and medium/large physician practices to respond to the changing environment (Daugherty, 2008).

### **Research Question and Hypothesis**

The research question examined in this study is: How did the rates of adoption of small and medium/large practices change among small and medium/large practices between 2000–2001

and 2004–2005, and did the gap between small and medium/large practices narrow or widen over this period?

To test this research question, the analyses conducted in this study examine the following hypothesis:

- H1: Small practices responded more strongly to the incentives generated by national policy intervention, payment incentives, and other general environmental conditions than medium/large practices and the gap in adoption between small practices and medium/large policies in implementing EHRs narrowed. This hypothesis will be tested using variables from Center for Studying Health System Change (CSHSC) – Community Tracking Study (CTS) Physician Survey (Center for Studying Health System Change, 2011).

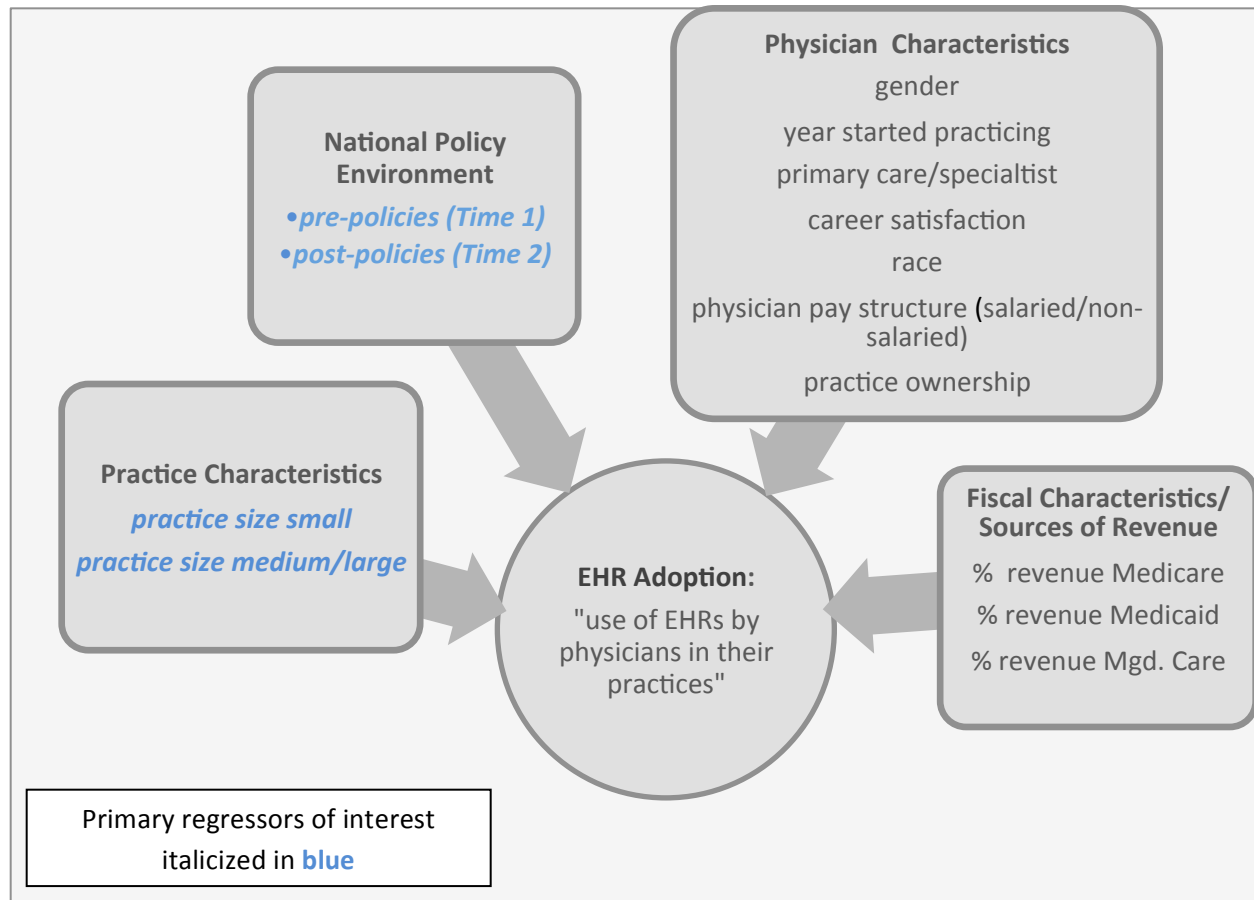
EHR Adoption =  $f$ (practice size, time pre- or post-policy intervention, gender, years practicing medicine, primary care vs. specialist, career satisfaction, race, physician compensation structure, practice owner, percentage of practice revenue from Medicare, percentage of practice revenue from Medicaid, percentage of practice revenue from managed care)

The effect of changes over time and the practice size are the primary regressors of interest.

### Specific Conceptual Model

Extracted from the overarching conceptual model presented in Chapter 1, and portrayed in Figure 4-1 below, analysis of the influence of practice and physician characteristics on small vs. medium/large physician practices' EHR adoption includes variables from three domains:

**Physician characteristics** such as gender, year began practicing medicine, primary vs. specialist physician, career satisfaction, and race; **Practice characteristics** such as practice size, and primary care/specialty; **Fiscal characteristics**, such as percent revenues from Medicare, Medicaid, and managed care. The model also includes the elements of the **National Policy Environment**, expected to influence adoption of EHR functionality over the time period studied, and a critical dimension of this study is whether the rate of adoption for small and medium/large practices of EHR functionality over this time period differs, controlling for the physician, practice and fiscal factors that might independently influence EHR adoption. This specific conceptual model (Figure 4-1) reflects the subset of variables available to include in the data analysis, constrained by what data is available through the surveys.



**Figure 4-1: Physician & Practice Characteristics in Relation to EHR Adoption**

**Methods**

Sources of Data:

This analysis uses data from the Center for Studying Health System Change – Community Tracking Study, Physician Survey 2000–2001 and 2004–2005. The data are made available through the Health and Medical Care Archive (HMCA) at the Inter-university Consortium for Political and Social Research (ICPSR). Sample sizes are: 2000–2001: n = 12,406 and 2004–2005: n = 6,628, and pooled dataset including both rounds, 19,034. The Center for Studying

Health System Change (HCS) – Community Tracking Study (CTS) Physician Survey has been conducted five times since 1996, in concert with Household and Employer Surveys conducted several times over the same time period. This survey is intended to take an in-depth look at issues and challenges physicians face in the rapidly changing health care system.

#### Study Cohort:

The CTS Physician Survey was conducted on nationally representative surveys of non-federal physicians who spend at least 20 hours a week in direct patient care. The survey was conducted in 1996–1997, 1998–1999, 2000–2001 and 2004–2005. This study analyzes the third (2000–2001) and fourth (2004–2005) rounds of data, as these data reflect the times before and after the national IT policy interventions, payment incentives, and other general environmental changes during the time period. Round 3 of the survey (2000–2001) includes responses from 12,406 physicians and Round 4 (2004–2005) includes responses from 6,648 physicians to questions about themselves and their practices. Gallup conducted data collection via telephone, focusing on physicians practicing in 60 randomly selected U.S. communities and to a supplemental national sample of physicians selected with stratified probability sampling. This supplemental sample was included in the survey to increase the precision of national estimates, allowing analyses to be conducted at both the national and community level. Primary care physicians were over-sampled in the site sample.

Questions regarding “use of computers” or information technology (IT) were added in the 2000–2001 and 2004–2005 survey rounds. Seven out of eight of the IT-related questions included in the 2000–2001 survey and the nine IT-related questions included in the 2004–2005 survey were the same, allowing for comparison of the EHR-related data between these two survey rounds.

(The first two rounds of the HCS-Physician Survey, conducted in 1996–1997 and 1998–1999, respectively, did not ask any IT-related questions.) The 2008 survey was changed to the 2008 Health Tracking Physician Survey, which asked IT-related questions as well, but used a different survey design, thus making comparison of the 2008 round with the earlier rounds infeasible (Center for Studying Health System Change, 2011).

#### Study Design: Measures

Dependent variable **IT Adoption Score**: The dependent variable developed for this study is a continuous variable measuring IT adoption by physicians for use in their practices; this measure was developed as described in Chapter 3. The study's dependent variable (IT Adoption) is composed of data from the surveys' seven (7) EHR-related questions, yielding a composite scale or IT Adoption Scale of 0–7. The seven (7) Yes/No IT-related questions in the surveys are as follows:

1. Computers used for treatment guidelines [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information about treatment alternatives or recommended guidelines?
2. Computers used for formularies [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information on formularies?



3. Computers used for preventive service reminders [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to generate reminders for you about preventive services?
4. Computers used for patient notes or medication lists [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to access patient notes, medication lists, or problem lists?
5. Computers used for writing prescriptions [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to write prescriptions?
6. Computers used for exchanging data with other physicians [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used for clinical data and image exchanges with other physicians?
7. Computers used for e-mail with patients [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to communicate about clinical issues with patients by e-mail?

Primary Variables of Interest—*Practice Size* and *Time 1/Time 2 Year*:

The primary regressors of interest in this study are: 1) *practice size*, measured by number of physicians in the practice; and 2) *Time 1 or Time 2* (Years 2000–2001 or Years 2004–2005, respectively) measured data from the CTS Physician Survey Round 3 and Round 4 datasets, respectively, and *DID policy* as the policy, reimbursement, and environmental changes variable.

The *practice size* variable is set up as a categorical variable: small practices (1–4 physicians) or medium/large practices (5+ physicians). This cut-off for the small practice size is supported by the literature, which indicates that not only are the greatest difficulties in adopting EHRs and lowest EHR adoption rates among the small physician practices, but the greatest number of practices are small practices as well—two-thirds of physicians in the U.S. work in solo or small practices (American Medical Association, 2001) (DesRoches C. , et al., 2008). The categorization of the sample into two categories based on these numbers is also supported by the literature (Ketcham, 2007; Burke-Bebee, 2008) (Burt, 2005). Additionally, the dataset for this study supports this cut-off, with 44.82% of physicians residing in Small practices and 55.18% of physicians residing in Medium/Large practices (Table 4-1). Because the research question and hypothesis center on the notion that practices with the greatest organizational infrastructural support may have more capacity to implement an EHR due to the availability of support resources, and smaller practices may not, this is the appropriate division and definition for the *practice size* data element and regressor of interest. The *Time 1/Time 2* (2000–2001/2004–2005) data element (*DID policy*) is an identifying variable of the policy change and maps to this study’s Hypothesis.

Other independent variables used in the analysis include:

Physician Characteristics:

*Gender (female)*: physician gender, female or male;

*Year began practicing medicine (yrbgnx)*: this variable is divided into 8 categories, with one referent category:

1996+ (referent):

1992–1995;  
1986–1990;  
1982–1985;  
1976–1980;  
1971–1975;  
1966–1970; and  
1965 or earlier

*Primary care or specialist (pcpflag)*: this variable identifies whether the physician is a primary care physician (family practice, general practitioner, pediatrician, other) or specialist (specialist or sub-specialist).

*Career satisfaction (careersat)*: this variable identifies whether the physicians is satisfied (very satisfied, somewhat satisfied) or dissatisfied (very dissatisfied, somewhat dissatisfied) with her or his career.

*Race (race)*: this variable identifies whether the physician is non-white or white, as the categories were collapsed because 78.8% of the samples were white.

*Physician compensation structure (salaried)*: this variable identifies whether the physician is salaried or non-salaried.

*Physician practice ownership (owner)*: this variable identifies whether the physician is an owner of the practice (full owner or partial owner) or not an owner.

#### Fiscal Characteristics

*Percentage revenue from Medicare (% Rev. MCARE)*: this variable identifies the percentage of revenues of the practice from Medicare.

*Percentage revenue from Medicaid (% Rev. MCAID)*: this variable identifies the percentage of revenues of the practice from Medicare.

*Percentage revenue from managed care (% Rev. MC)*: this variable identifies the percentage of revenues of the practice from managed care.

### **Data issues**

Of the pooled dataset, a total of 255 data elements were missing from the two surveys, so the total pooled sample was reduced from 19,034 to 18,779, eliminating the missing data with a *sample\_use, missing* program during the data cleaning process. Survey weights were not used, in order to avoid problems in bootstrapping confidence intervals. Variables were not transformed for this analysis.

### **Study Design**

This analysis uses the Difference-in-Differences (DID) framework to estimate the difference in adoption rates between small and medium large practices over the 2001-2004 time period when national policy interventions, payment incentives, and environmental conditions created substantial incentives to increase EHR adoption. While DID is often used in the comparison of one environment with a characteristic to another without it, DID is used in this analysis to mathematically estimate the difference in the difference between small and medium/large practices in their EHR adoption rates. The essence of this use is rooted in disparities research. In this study, small practices are assumed and hypothesized to have greater challenges in adopting EHR systems than medium/large practices. This assumption is borne out by the literature. This study design was selected since DID lends itself to estimating the differences between small and medium/large practices in adoption over time, controlling for their baseline rates of adoption.

### **Statistical Analysis**

Descriptive statistics, including characteristics of IT Adoption Score, Time 1 and Time 2 datasets, pooled dataset, physician characteristics, practice characteristics and fiscal characteristics were summarized with means and standard deviations of continuous variables and counts and percentages for categorical variables and are presented in Table 4-1.

The differential rate of adoption between small and medium/large practices was then estimated using the DID method to determine whether there was a significant difference in IT adoption scores Time 1 and Time 2 and whether there were changes in the differences between the Time 1 and Time 2, small and medium/large size physician practices. This was performed to detect any effect on the differences between these two groups, as small practices have significantly lower adoption rates than larger practices (Bates, 2005) (Burke-Bebee, 2008) (DesRoches C. , et al., 2008). Ordinary Least Squares (OLS) models were performed without and with DID, both with cluster correction. As discussed below, a greater increase in adoption was found among the medium/large practices than small practices, suggesting that small practices are disadvantaged in their abilities to adopt EHRs.

Estimated DID:

$$y = \beta_0 + \beta_1 * small + \beta_2 * post + \beta_3 * post * small$$

The interpretation of these coefficients is summarized in the Results section below; results are presented in Table 4-2. Bootstrap confidence intervals are presented in Table 4-3.

To grasp the magnitude of the differences, predicted mean values of IT Adoption Scores were calculated for small practices Time 1 and Time 2 intervention, for medium/large practices pre- and post-policy intervention, and the changes in IT Adoption Scores, as presented in Table 4-4.

DID Construct Adoption	Pre-policies – Time 1	Post-policies – Time 2	
Small Practices (1)	$\beta_0 + \beta_1$	$\beta_0 + \beta_1 + \beta_2 + \beta_3$	$\Delta_{small_{pre-post}}$
Medium/Large Practices (0)	$\beta_0$	$\beta_0 + \beta_2$	$\Delta_{med/large_{pre-post}}$

Based on the equation:

DID = (small@post-policy Time 2 – small@pre-policy Time 1) – (medium/large@post-policy Time 2 – medium/large@pre-policy Time 1) (Rose, 2005)

$$(B - A) - (D - C) = DID$$

$$[(b_0 + b_1 + b_2 + b_3 - (b_0 + b_2))] - [b_0 + b_1 - (b_0)] = DID$$

The bootstrap for coefficient of the interaction effect that represents the DID was performed to derive confidence intervals (i.e., normal, percentiles, and bias corrected). The bias corrected yielded the 95% confidence interval of [-0.497, -0.266], not crossing zero (0), thus the estimate is statistically significant (Table 4-3). Descriptive statistics were calculated for continuous and categorical variables.

## Results

Descriptive statistics: Descriptive statistics are presented in Table 4-1. Summary statistics of continuous variables include: 1) the dependent variable (IT Adoption) for the pooled sample, 2000–2001, and 2004–2005; 2) percent practice revenue from Medicare; 3) percent practice revenue from Medicaid; and 4) percent practice revenue from Managed Care. Also displayed in Table 4-1 are tabulations of categorical variables, including: small vs. medium/large practices; year Time 1 (2000–2001; Time 2 (2004–2005); female vs. male (referent female); year in categories the physician began practicing (referent 1965+); primary care vs. specialist (referent primary care); career satisfaction (referent satisfied); physician race non-white/white (referent white); physician salaried (referent salaried); physician owner of practice (referent owner). IT Adoption Score for the pooled sample (2000–2001 and 2004–2005) was 2.37 (SD 1.93); for 2000–2001, it was 2.11 (SD 1.85) and 2004–2005 2.85 (SD 1.99). About forty-five percent (44.6%) of practices were small (1-4 physicians). About one-quarter (27%) of physicians were female. More than half (57%) of physicians were in primary care vs. specialties. The vast majority (82.2%) of physicians were satisfied. About one-fifth (21.2%) of physicians were non-white. Slightly more than half of physicians were salaried (52%) and were practice owners (52.2%). Percent revenues from Medicare, Medicaid, and managed care were about thirty percent (29.9%), sixteen percent (15.9%) and forty-five percent (44.8%), respectively.

### Multivariate Statistics (Table 4-2)

Specifications performed (OLS, OLS with interaction DID, unstructured): In the analysis to determine evidence of a policy, payment incentive, or environmental impact between Time 1 and

Time 2 and whether medium/large practices adopted EHRs more than small practices, OLS with cluster correction, with no interaction, was performed initially. This was to correct for physicians (cluster) that are repeated in the two survey datasets, Time 1 and Time 2 respectively. This OLS estimation served as a baseline, and then progressed to the OLS with interaction DID estimation to determine whether the policy interventions, payment incentives, along with the environmental influences had an effect on EHR adoption among small vs. medium/large practices during this time period. The OLS with interaction DID was estimated to measure and reveal the effect of the policy (DID). In other words, it reflects on the question posed in the hypothesis: did policy intervention, payment incentives, and environmental change encourage or help create a positive change (i.e., close the gap) in IT Adoption scores between Time 1 and Time 2 among small vs. medium/large practices? For OLS with no interaction as a baseline, OLS with DID was run to detect the difference in effect on small vs. medium/large practices between Time 1 and Time 2 with the policy intervention, controlling for independent variables and within the broader context of other influences in the environment in this time period.

### **Description of Results for Main Regressors**

Primary Regressors of Interest (*pre- and post-policy (Year 1 vs. Year 2); practice size, (small vs. medium/large practices)*) - Results show in the pooled OLS, that small practices were on average 0.623 points lower (-0.623) on the IT adoption scale than medium/large practices, controlling for other physician, practice, and fiscal variables. This indicates that medium/large practices adopted EHR functionality at a greater rate than small practices. The DID model evaluated changes in EHR adoption rates between the two size category practices. In Time 1, the small practices were, on average, 0.493 points lower than the medium/large practices on the IT adoption scale, controlling for other covariates. Then, while both small and medium/large practices increased



their EHR adoption rates between Time 1 and Time 2, medium/large practices EHR adoption rates increased more than small practices. The gap in adoption between smaller practices vs. medium/large practices widened from Time 1 to Time 2, not narrowed; thus, disparity between small and medium/large practices increased. This result shows that in the general environment subject to other influences, the policies and payment incentives, on average, increased EHR adoption of both small and medium/large practices, but and policy or payment incentive effect of reducing the disparity between small practices and medium/large practices, controlling for the independent characteristics, did not happen. Policy intervention, payment incentives, and environmental conditions created the effect of encouraging or inspiring EHR adoption in physician practices generally, but didn't close or narrow the gap between small and medium/large practices in their IT adoption scores. Rather, the gap widened.

These results reflect the greater difficulties that small practices have in adopting IT and EHRs as compared to medium/large practices. Controlling for other variables, small practices' IT adoption rates were on average less improved with the policies and incentives implementation than medium/large practices' improvements in EHR adoption rates, in the context of other environmental occurrences. Thus the policies and payment incentives did not result in small practices gaining on or overcoming disadvantages they have in pursuing EHR adoption. This gives rise to new questions about why this might be occurring, possibly related to less infrastructure supporting these EHR implementations in small vs. medium/large practices.

The predicted mean values of IT Adoption Scores Time 1 and Time 2 interventions (Table 4-4) show a mean positive change of 0.478 (1.714 to 2.192) for small practices and a mean positive change of 0.887 (2.445 to 3.332) for medium/large practices following the policy interventions.

## **Brief summary of results for other covariates**

### Physician characteristics:

*Female:* Being a female was associated with a lower IT adoption score, on average, than for males in the OLS estimate (-0.264 points) and in the OLS with interaction (DID) (-0.262 points) using the pooled sample, indicating the policy, payment incentives, and environmental conditions did not induce or improve IT adoption among female physicians; these results indicate that being female was associated with lower adoption scores, on average with effects of the policy, payment incentives, and environmental conditions, controlling for other independent variables.

*Year began practicing medicine:* The year a physician began her or his practice of medicine lost its effect for the 1991–1995 group between the OLS with no interaction (significant at  $p < 0.001$ , 0.059 on the IT adoption scale) vs. OLS with interaction (DID) (0.047), while the physicians beginning their practice of medicine “between 1965 and earlier” became significant at the  $p < 0.001$  level with OLS with interaction (DID) estimating the effect of the policy intervention on this group on average, controlling for other physician, practice and fiscal characteristics.

*Primary care vs. specialty physicians:* In the OLS analysis the IT adoption scale for primary care physicians was 0.191 points lower than their specialist counterparts, controlling for the other characteristics; OLS with interaction DID results show on average an IT adoption score for primary care physicians of 0.188 points lower than their specialist counterparts controlling for other characteristics. These results are significant at the  $p < 0.001$  level.

*Career satisfaction:* For physicians satisfied with their careers, results show on average a higher IT adoption score (0.163 points), in the OLS with no interaction estimates; the OLS with

interaction DID show on average a higher IT adoption score (0.161 points) than the scores for those physicians not satisfied with their careers, controlling for other characteristics (significant at  $p < 0.001$  level). These results show that while career satisfaction has a positive effect on EHR adoption scores, this effect did not change markedly with the policy intervention, payment incentives, or environmental conditions.

*Race:* Non-white physicians were estimated to have on average higher IT adoption scores (0.111 points) than their white counterparts in the OLS without interaction, as well as higher IT adoption score (0.111 points) in the OLS with the interaction DID analysis; both results are significant at the  $p < 0.001$  level.

*Physician pay structure:* Salaried physicians are estimated in the OLS without interaction analysis to have on average higher IT adoption scores than their non-salaried counterparts (0.459 points), controlling for other characteristics, significant at the  $p < 0.001$  level. Salaried physicians are estimated in the OLS with interaction DID analysis to have on average a higher IT adoption (0.461 points) than their non-salaried counterparts, controlling for other covariates, also significant at the  $p < 0.001$  level. IT adoption scores for salaried physicians are on average significantly higher than non-salaried physicians.

*Practice ownership:* Physicians who are also owners in their practices are estimated to have similar IT adoption scores on average (-0.0004 in OLS without interaction analysis and 0.004 in OLS with interaction DID analysis, controlling for other variables).

#### Fiscal Characteristics of Practices

*Percent (%) revenue from Medicare:* The effect of “percent revenues from Medicare” is that a 1% increase in Medicare expenditure leads to an increase in the IT adoption score of about 0.002

points on average in the OLS without interaction model and the same effect on the OLS with interaction DID analysis, both results significant at the  $p < 0.01$  level, controlling for other independent variables in the model.

*Percent (%) revenue from Medicaid:* The effect of percent revenues from Medicaid is for a 1% increase in percentage of Medicaid revenue leads to an increase in the IT adoption score of about 0.003 points on average in the OLS without interaction model, significant at the  $p < 0.01$  level, and on average a 0.002 increase on the IT adoption scale in the OLS with interaction DID analysis, also significant at the  $p < 0.01$  level, each controlling for other variables in the model.

*Percent (%) revenue from Managed Care:* The effect of “percent revenues from managed care” is for a 1% increase in percentage of managed care revenues leads to an increase in the IT adoptions score (0.003 points) on average in the OLS without interaction model, significant at the  $p < 0.001$  level; and a 1% increase in managed care revenues leads to an increase in the IT adoption score on average (0.005 points) in the OLS with interaction DID model, controlling for other factors in the model and significant at the  $p < 0.001$  level.

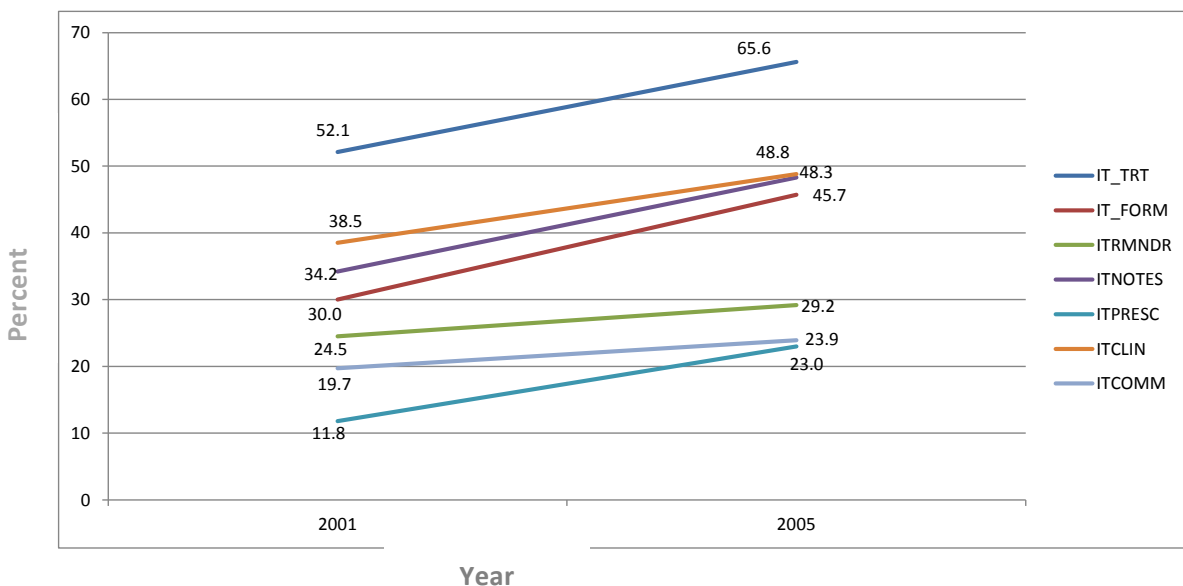
### Other Statistics

*Post-estimation difference-in-difference (DID) Bootstrap:* The DID policy variable, at a 0.06 standard deviation, shows a 95% confidence interval of -0.497, -0.266, bias corrected. Post-estimation predicted mean Time 1 and Time 2 intervention results (Table 4-5) to show a mean positive change in small practices (from 1.714 to 2.192) in the IT Adoption Scale following the policy intervention (an increase of 0.478 points) and a mean positive change in the IT Adoption Scale in large practices (from 2.445 to 3.332) in medium/large practices from Time 1 to Time 2 (an increase of 0.887 points). This finding provides evidence of a positive effect of the Time 1 to

Time 2 policy, payment, and environmental changes. This finding is consistent with literature indicating EHR adoption is beneficial from quality, efficiency and access standpoints (Blumenthal D. M., 2009)) for small practices, which reduces the disparity associated with small practice EHR adoption, but an overall benefit as well, since medium/large practices also increased their adoption as a result of the policy intervention.

Figure 4-2: IT Functionality Changes over Time in the Pooled Sample shows the change from 2000–2001 to 2004–2005 in the adoption of each of the seven EHR functionalities. In all cases, overall adoption increased, more for some than for others. In no case, did the lines cross, meaning the relative position based on adoption of the seven functionalities by physicians in the pooled sample did not change. In decreasing order from most to least adopted, the EHR functionalities adopted were: IT\_TRT (treatment guidelines); ITCLIN (exchange of clinical data and images with other physicians); ITNOTES (patient notes or medication lists); IT\_FORM (formularies); ITRMNDR (preventive service reminders); ITCOMM (communicate with patients); and ITPRESC (writing prescriptions).

**Figure 4-2: IT Functionality Changes over Time in the Pooled Sample**



## **Discussion**

Findings from this study suggest that the disparities between small and medium/large practices were not narrowed as a result of the policy interventions, payment incentives, and overall environmental conditions from Time 1 to Time 2. According to DID analysis, the study findings provide evidence that such policy interventions, payment incentives, and environmental conditions have significant effect on both small and medium/large practices, but the gap in adoption between small and medium/large practices actually increases as the EHR adoption cycle matures. The policy intervention, payment incentives, and environmental conditions did not make up the difference and thus did not reduce the disparity between small and medium/large practices in implementing electronic health records (EHRs); in fact, among other influences at the time, the gap widened between small and medium/large practices adoption of EHR systems. Post-estimation calculations of the predicted value of pre- and post-small and medium/large practices (Table 4-4) anchor the difference-in-differences estimates (Table 4-2) in predicted values. This provides evidence that actual predicted mean values for IT adoption scores improved overall, but that the gap increased between the small and medium/large practices in EHR adoption in the context of policy interventions, payment incentives, and overall environmental changes in the health care industry.

Also, interestingly, while practices did increase EHR adoption rates in the context of policy intervention, payment incentives, and environmental conditions (especially medium/large practices), control variables such as years in gender, practice, career satisfaction, physician compensation structure, race, and sources of revenue did not vary significantly in correlation with IT adoption from Time 1 to Time 2.

Overall, this analysis provides evidence that during the time period 2000–2005, under Bush policies implemented in 2003 with the Medicare Prescription Drug Improvement and Modernization Act (MMA) of 2003 and establishment of the Office of the National Coordinator (ONC) for Health Information Technology (officially in 2004), payment incentives, and environmental conditions, physician practices of all sizes increased their EHR adoption. The analysis also shows that medium/large practices were more likely to adopt in the overall context of the time period, controlling for physician characteristics, practice characteristics and fiscal characteristics. In other words, policy intervention, payment incentives, and environmental conditions are associated with innovation among all practices but moreso in medium/large than small practices, thus not having an effect of reducing the disparity in EHR adoption between small and medium/large practices, nor changing the relative position of adoption of each of the EHR functionalities, one to another.

### **Study Limitations**

Data for this study were gathered through self-reported data from physician surveys. Data were also cross-sectional, limiting the ability to make causal inferences between study variables. Although missing data were confined to a small number of variables, greater issues with missing information may be related to omission of geographic data and data on population density where the practices are located. The study does not include variables giving a more finite definition of financial incentives that might have been provided through the national policy as incentive to implement in the practices surveyed. (It should be noted, however, that the financial incentives associated with these earlier health information policies paled in comparison to the incentives recently provided to physicians and hospitals to implement “meaningful use” EHR functionality as part of Public Law 11–5: The 2009 American Recovery and Reinvestment Act.) The earlier

Bush Administration incentives came in the form of seed money grants of \$50,000, up to a total of \$2,000,000 for HIT demonstration projects; this is compared to ARRA's \$36 billion of financial incentives to practices and hospitals achieving "Meaningful Use" of EHRs (Orszag, 2008). In addition, as the EHR adoption curve matures, the "innovativeness" of early adopters may wane and results may not be generalizable to future cohorts.

### **Clinical and/or Policy Implications and Future Research Directions**

This study's results provide evidence that initial national policy, payment incentives, and environmental conditions supporting EHR adoption had a significant effect, but did not narrow the disparities gap or disadvantage small physician practices face compared to their medium/large practice counterparts with EHR adoption for use in their practices. Implications of these results are that additional or current policies specifically targeted to small practice sizes are appropriate since the small practices appear to need the most support. The study also provides input into methods that might be useful to dissect additional adoption issues and reduce other EHR adoption disparities, which can then be used to refine targeted practices and interventions to further improve EHR adoption results. National funds could be spent more carefully based on evidence gained from further research to assure EHR adoption support funding has increased impact and reduced waste.

Physician training programs can be enhanced to inform physicians of potential considerations when setting up their practices that may improve their chances of successful EHR adoption. Also, certain physician types can be provided customized support for encouraging EHR adoption, such as female physicians and specialists, in addition to small practices. Given that EHR and IT adoption rates are lowest in small practices, which are the most common practice



size in the U.S. (Hing, Burt, & Woodwell, 2007), future research examining the continued impact of national policy on EHR adoption could inform whether this effect is sustained.

Additionally, with major incentives and penalties added to national policy on EHR adoption through the Health Information Technology for Economic and Clinical Health (HITECH) Act, part of the American Reinvestment and Recovery Act (ARRA), future research should closely examine the effect and direction of the impact of this policy, in order to increase its benefits and contribution to the social good and improvements in quality and cost-effectiveness of health care. Finally, future research should examine the effect of ARRA's HITECH on inducing innovation in the form of EHR adoption by small vs. medium/large physician practices and whether these policies assist in closing the disparities gap between small vs. medium/large practices in HIT adoption and implementation.

## Tables

**Table 4-1: Descriptive statistics from surveys of small and medium/large physician practices regarding use of electronic health records (EHR). CSHSC: CTS Round 1: 2000–2001, Round 2: 2004–2005.**

Variables	Pooled Sample* (N = 18,779)				2000-2001* (N=12,254)	2004-2005* (N = 6,525)
	Mean (SD)	Min/Max	N	Percent	Mean (SD)	Mean (SD)
IT Adoption Score	2.37(1.93)	0 / 7			2.11 (1.85)	2.85 (1.99)
Practice Size						
Small (1-4)			8,383	44.6%		
Med/large (5+)			10,396	55.4%		
Female			5,076	27.0%	3,275 (26.40%)	
Year began practice						
1996+ (referent)			2,430	12.9%	2,458 (19.81%)	
1991–1995			3,041	16.2%	2,263 (18.24%)	
1986–1990			3,413	18.2%	2,131 (17.18%)	
1981–1985			2,936	15.6%	1,950 (15.72%)	
1976–1980			2,521	13.4%	1,546 (12.46%)	
1971–1975			1,851	9.9%	943 (7.60%)	
1966–1970			1,146	6.1%	466 (3.76%)	
1965 or earlier			1,441	7.7%	649 (5.23%)	
Primary care vs. Spec.						
Primary Care			10,831	57.7%	7,673 (61.85%)	
Specialist			7,948	42.3%	4,733 (38.15%)	
Career satisfaction						
Satisfied			15,779	82.2%	10,064 (81.12%)	
Dissatisfied			3,347	17.8%	2,318 (18.68%)	
Race						
Caucasian			14,799	78.8%	9,774 (78.78%)	
Non-Caucasian			3,980	21.2%	2,503 (20.18%)	
Phys pay structure						
Salaried			9,946	53%	6,597 (53.18%)	
Not salaried			8,833	47%	5,809 (46.82%)	
Practice ownership						
Owner			9,801	52.2%		
Non-owner			8,978	47.8%		
Fiscal characteristics						
% Rev. MCARE	29.9(22.9)	0/100				
% Rev. MCAID	15.9 (18.3)	0/100				
% Rev. MC	44.8 (28.0)	0/100				

Note: \*Limited to those with complete data.

**Table 4-2: Difference-in-differences (DID) model of the effect of policy on use of electronic health records (EHR) by small and medium/large physician practices: CSHSC CTS: 2000–2001, 2004–2005.**

	Pooled Dataset (N = 18,779) IT Adoption OLS w/no interaction with cluster correction			Pooled Dataset (N = 18,779) IT Adoption OLS w/interaction DID with cluster correction		
IT Adoption Score	Coefficient	SE	95% CI	Coefficient.	SE	95% CI
Practice Size Small	-0.623***	0.031	[-0.683,-0.562]	-0.493***	0.035	[-.562, -.423]
DID (policy) Year (2004–2005)	0.746***	0.0308	[0.686, 0.806]	-0.384***	0.057	[-0.495, -272]
Female	-0.264***	0.0323	[-0.328 -0.201]	-0.262***	0.032	[-0.325, -0.2]
Year began practice						
1996+ referent						
1991–1995	0.059***	0.05	[-0.039, 0.157]	0.047	0.05	[-0.051,0.145]
1986–1990	0.026	0.05	[-0.072, 0.124]	0.010	0.05	[-.088, .108]
1982–1985	0.012	0.052	[-0.09, 0.114]	-0.002	0.052	[-0.104, 0.1]
1976–1980	-0.021	0.055	[-0.13, 0.087]	-0.037	0.055	[-0.145,0.071]
1971–1975	0.015	0.061	[-0.104, 0.133]	-0.000	0.060	[-.119, .118]
1966–1970	0.125	0.070	[0-.262, 0.016]	-0.135	0.070	[-.273, .002]
1965/earlier	-0.426	0.065	[-.554, -0.298]	-0.43***	0.065	[-.557, -.302]
Primary vs. Specialty						
Primary Care	-0.191***	0.028	[-0.245,-0.136]	-0.188***	0.028	[-.242, -.134]
Career Satisfaction						
Satisfied	0.163***	0.036	[0.093, 0.233]	0.161***	0.036	[0.091, 0.231]
Race						
Non-white	0.111**	0.035	[0.043, 0.179]	0.111**	.035	[0.043, 0.178]
Physician pay structure						
Salaried	0.459***	0.034	[0.393, 0.525]	0.461***	0.034	[0.395, 0.527]
Practice ownership						
Owner	-0.0004	0.0366	[-0.072, 0.071]	0.004	0.037	[-0.068,0.076]
Fiscal characteristics						
% Revenue MCARE	0.002*	0.001	[0.0004, 0.003]	0.002*	0.001	[0.000, 0.003]
% Revenue MCAID	0.003*	0.001	[0.001, 0.004]	0.002**	0.001	[.001, 0.004]
% Revenue MC	0.005***	0.001	[0.004, 0.006]	0.005***	0.001	[0.004, 0.006]

<b>Table 4-3: Post-estimation Difference-in-differences (DID) Bootstrap</b>			
Variable	Reps	SE	95% Conf. Interval
<b>DID</b>	1000	0.06	[-0.501, -0.266] (N)
-0.384			[-0.495, -0.265] (P)
			[-0.497, -0.266] (BC)

<b>Table 4-4: Post-estimation predicted means Round 1 and Round 2 IT Adoption Scores for small and med/large practices: CSHSC; Time 1 2000–2001, Time 2 2004–2005.</b>					
Variable	N	Mean	Std. Dev.	Min	Max
<b>Time 1 small practices</b>	5620	1.714	0.3224	0.485	0.2.603
<b>Time 1 med/large practices</b>	6635	2.445	0.2981	1.234	3.247
<b>Time 2 small practices</b>	2763	2.192	0.3381	1.143	3.206
<b>Time 2 med/large practices</b>	3762	3.332	0.321	2.246	4.18

<b>Table 4-5: Post-estimation difference-in-differences (DID) between small and medium/large physician Time 1 (2000-2001) and Time 2 (2004-2005)</b>			
<b>EHR Adoption Changes Over Time</b>			
	Time 1	Time 2	Differences
<b>Small</b>	1.714	2.192	-0.478
<b>Medium/Large</b>	2.445	3.332	-0.887
<b>Difference</b>	-0.731	-1.140	-0.409

Adoption of Electronic Health Records  
by Physicians for Use in Their Practices

Chapter 5

Panel Analysis of Physician Adoption of  
Electronic Health Record System Capabilities

**Introduction**

This chapter analyzes changes, rates, and physician and practice characteristics in adoption of EHR functionality among a panel of physicians created from the restricted datasets from the Center for Studying Health System Change Community Tracking Study – Physician Survey Round 3 (2000–2001) and Round 4 (2004–2005). This panel was created to analyze the association of the independent variables reflecting physician and practice characteristics to IT Adoption among the same physician respondents to create a more powerful analysis. Chapter 4 examined overall rates of adoption among a pooled dataset created by combining the public datasets from the same survey and rounds. This chapter aims to examine EHR functionality adoption and de-adoption among this panel of physicians, and how does adoption vary by EHR

functionality and overall IT Adoption Score. It also examines physician and practice-based drivers of adoption of EHR functionalities using the IT Adoption Score that was developed and described in Chapter 3 of this dissertation.

The backdrop to this chapter's analysis is the motivation to understand early trends in adoption of Electronic Health Record (EHR) systems by physicians in office-based practices. Those interested in the EHR adoption phenomenon include multiple actors in the U.S. health system, including providers, patients, government, payers, researchers, and those participating in the Health Information Systems and Technology (HIS) industry such as vendors and consultants. (Ashish K. Jha, 2010) Recent government policies including the American Recovery and Reinvestment Act (ARRA) Health Information Technology Economics and Clinical Act (HITECH Act) and the Affordable Care Act (ACA) are changing the landscape of medical practice in this country—physicians in office-based practices are being encouraged through incentive programs to adopt EHR systems for use in their practices (Blumenthal D. M., 2009). Additionally, this chapter reflects the results of this analysis within the context of Rogers' Diffusion of Innovation Theory.

In this study, analysis of the data from a panel of surveyed physicians describes the types of changes in EHR adoption patterns occurring over time as well as potential drivers of those changes, and goes beyond straightforward adoption statistics from cross-sectional analyses reflecting adoption statistics for a particular population at a point in time (Center for Studying Health System Change, 2003) (Center for Studying Health System Change, 2006).

In addition to cross-sectional analyses, this study examines trends of adoption of six years among a nationally representative panel of physicians and practices. The panel consists of physician

respondents who participated in both the Center for Studying Health System Change Community Tracking Study – Physician Survey Round 3 (2000–2001) and Round 4 (2004–2005). The same seven IT-related questions were asked in each of these survey rounds, thus providing consistent IT-use variables for measuring EHR-adoption using the panel dataset.

This panel analysis of trends in rates and drivers of EHR adoption informs the understanding of differences in changes over time based on size of practice and other provider and practice characteristics. Extending through the years 2000–2006, this dataset provides the opportunity for descriptive analysis that provides: 1) a backdrop for understanding the impact of the government’s major investment through HITECH to stimulate the adoption of EHR systems; and 2) an opportunity to determine where the panel’s adoption of EHR functionality falls on Roger’s Diffusion of Innovation Curve (Boston University School of Public Health, 2013) (Rogers, 1981). The HITECH Act of 2009 has allocated the investment of \$27 billion in incentives and other financial support of the implementation of EHR systems in physician practices and hospitals (Shilling, 2011). The Federal government’s assumptions fueling this investment include the premise that physician practices, especially smaller-size ones, need financial incentives to spur and support them to implement these systems, since smaller practices have struggled to prioritize these complex projects, generally lacking the resources for the additional effort and infrastructure associated with EHR adoption. (DesRoches C. M., 2015) (Shilling, 2011)

This chapter presents two main analyses of EHR adoption trends over the six-year period, describing:

1. Whether adoption or de-adoption of EHR functionalities has occurred and how do these vary by each of the seven EHR functionalities; and

2. Which practice and physician-based characteristics that serve as drivers of adoption and de-adoption of EHR functionality, measured by the mean IT Adoption Score for the full panel, small practice, and medium/large practice samples.

This pre-ACA and pre-HITECH panel analysis provides a baseline for studying similar trends among physician practices during post-ACA and post-HITECH time periods.

This study informs the discussion among providers, policy-makers, researchers, and other interested parties regarding trends and changes in physician practice EHR adoption behaviors in the pre-HITECH and pre-ACA environment. It also helps clarify assumptions and expectations for EHR adoption behaviors in the ACA/HITECH era, sets the stage for understanding the impact of ACA and HITECH on EHR adoption trends, and provides insight into ways to further direct government incentives, investments, and programs to achieve the objectives of the HITECH programs. Analysis of panel data reveals types of changes in EHR adoption occurring over a period of time among the same group of physicians, and describes the association of these changes to physician and practice characteristics including payment mechanisms. This may provide insight into where EHR adoption expectations and support programs may be vulnerable to drivers of adoption or de-adoption based on particular physician characteristics or practice conditions. This study thus informs policy directing the sustained application of HITECH funds and support to the physician practice environments in which the hoped-for EHR adoption occurs, and provides perspective on the appropriateness and timing of the shift from incentives to penalties for non-compliance with EHR adoption criteria targets set by the government's Office of the National Coordinator for HITECH (DesRoches, Audet, Painter , & Donelan, 2013)



## **Research Question and Hypothesis**

This analysis of panel survey data examines trends in the EHR adoption behavior among a nationally representative panel of physicians, according to their use or lack of use of seven EHR-related functionalities.

The questions driving this panel analysis include: What trends do these data reflect in adoption of EHR capabilities by physicians for use in their practices? Do associations exist between physician and practice characteristics and levels of implemented IT capabilities over time? How does practice size affect the level of IT adoption by physicians over time and how do small and medium/large practices compare in these trends? Does this panel analysis provide evidence of catch-up between slower-adopting small and faster-adopting medium/large practices (identified in the difference-in-differences analysis of the pooled sample of these same data sets in Chapter 4)? What does the panel analysis reveal about adding, reducing, or retaining EHR functionality among small practices, medium/large practices, and the total panel?

The study has three possibilities: 1) the EHR adoption gap between small and medium/large practices is narrowing and small practices with lower rates of adoption catch up over time; 2) the gap in adoption rates between small and medium/large practices widens over time; or 3) small and medium/large practices both increase the adoption of EHR functionalities and maintain the same relative position over time. Arguments can be put forth for each of these possibilities and so this study allows the data to empirically tell us which of the three possibilities occurs among this panel of physicians.

Hypotheses: The following Hypotheses are tested in this analysis.

The Hypothesis regarding overall EHR adoption within the panel is: Both small and medium/large groups of practices within the panel increase EHR adoption over time.

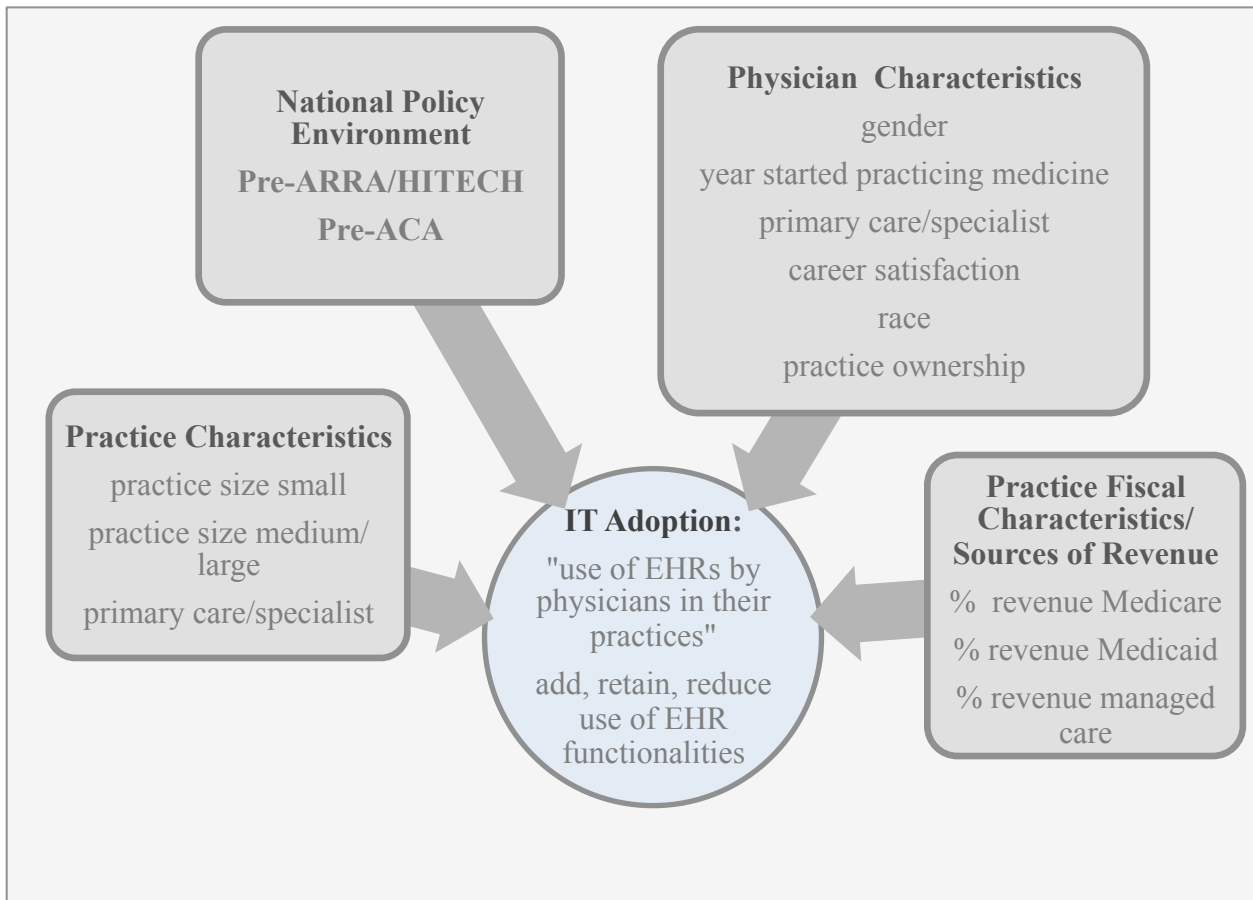
The Hypothesis focusing on differences between Small and Medium/Large-size physician practices is: Small-size physician practices (four or fewer physicians) will adopt fewer EHR capabilities than medium/large practices (five+ physicians) over time.

An associated Hypothesis targeted at physician and practices characteristics is: In the overall context of the regulatory, reimbursement, and other environmental conditions, predictors or drivers associated with physician adoption of EHR functionalities will be different in Small Practices than Medium/Large Practices. Because larger practices have greater support infrastructure which puts less burden on individual physicians, EHR adoption in medium/large practices will be driven by individual physician characteristics less so than EHR adoption in small practices. Thus predictors or drivers of EHR adoption among small physician practices will vary from those associated with EHR adoption among medium/large physician practices.

### **Specific Conceptual Model**

The conceptual model supporting this analysis reflects four main elements associated with adoption of EHR capabilities in office-based physician practices through the six-year time period from 2000–2001 to 2004–2005. The model represents the outcome measure “IT Adoption,” influenced by independent variables including key physician characteristics, and practice characteristics including financial parameters, in the context of the national policy environment at the time of the surveys. Key Physician Characteristics include gender, race, year began practicing medicine (a proxy for physician age), primary care or specialist, career satisfaction, ownership status, and percentage of revenue from Medicare, Medicaid, and Managed Care. The

National Policy Environment during the two survey rounds for years 2000–2001 and 2004–2005 is pre-ARRA/HITECH and pre-ACA. Practice Characteristics include practice size (small (1–4 physicians) or medium/large (5+ physicians)) and Fiscal Parameters including physician ownership status, and percentages of revenue from Medicare, Medicaid, and managed care.



**Figure 5-1: Conceptual Model of Physician Panel Analysis 2000–2001 and 2004–2005**

## Methods

IRB approval for this study was attained in June 2012.

Data Source:

The source of the restricted datasets used for this panel analysis is the Center for Studying Health System Change – Community Tracking Study (CTS) Physician Survey 2000–2001 and 2004–2005, funded by the Robert Wood Johnson Foundation. The CTS is a large-scale study designed to longitudinally track changes in the health care system and the effects of those changes on the lives of people. The CTS consists of three branches consisting of the Household Survey, the Health Plan Survey, and the Physician Survey. Surveys were conducted in two-year intervals, beginning in 1996. Sixty cities (51 metropolitan and nine non-metropolitan) were randomly selected and used in the CTS as a reflection of the entire nation.

The data are made available through the Health and Medical Care Archive (HMCA) at the Interuniversity Consortium for Political and Social Research (ICPSR). ICPSR is a unit within the Institute for Social Research at the University of Michigan. The data used for this analysis comes from two rounds of the Physician Survey, which was administered to physicians in the sixty CTS sites and to a supplemental national sample of physicians.

The Physician Survey conducted in 2000–2001 comprised Round 3 of the CTS Physician Survey, and the 2004–2005 Physician Survey, Round 4. The first two rounds did not include questions about information technology (IT). Thus, the 2000–2001 and 2004–2005 surveys are the first two of the CTS Physician Survey containing data that enable panel analysis of EHR adoption. (Note: The 2008 round of the CTS Physician Survey was changed to the Health Tracking Physician Survey, and which changed the survey format and methodology thus those data cannot be compared to the data used in this analysis.)

In Round 3 of the CTS Physician Survey (2000–2001), 12,406 physicians responded; in the Survey's Round 4 (2004–2005), 7,768 physicians responded. Of the 7,768 respondents in Round

4 (2004–2005), 4,428 also participated in Round 3 (2000–2001). Thus, this study analyzes data from the panel of 4,428 physicians who participated in both the 2000–2001 and 2004–2005 rounds of the survey. The panel sample of 4,428 is further restricted by certain changes within the panel physicians such as changes in the physician location and differences greater than ten in practice size (i.e., the number of physicians comprising a practice). Only seven EHR-related questions used in both rounds are included as variables in this panel analysis, although the 2004–2005 survey alone contains a few additional IT-related variables beyond those seven, such as “IT used to exchange clinical data/images with hospitals/labs” (ITHOSP) and “Uses IT for information on patient drug interactions” (ITDRUG). These additional IT-related variables are not included in this panel analysis; only data from the seven questions used in both Round 3 and Round 4 among the physicians responding to both surveys are used for this panel analysis.

**Measures:**

Primary Variable of Interest: IT Adoption Score (total\_it) is the primary variable of interest, analyzed according to a number of sub-groups (Full panel, Small Practice, and Medium/Large Practice samples) and independent variables. IT Adoption Score is a continuous variable from 1–7, and for groups the score is averaged. One point is given for every “yes” answer to each of the seven questions whether the physician uses each of the seven IT capabilities in her or his practice. This variable was also used to create a new variable “dtotal\_it”, reflecting the change in IT Adoption between the baseline (Round 3: 2000–2001) and second (Round 4: 2004–2005) time periods.

Outcome measure: Measuring EHR adoption is a complex undertaking; Chapter 3 is devoted to that topic. For this panel dataset and analysis, the outcome measure IT Adoption Score (total\_it)

is a continuous variable from zero to seven (0–7), with one point counted for every “yes” answer by physician respondents about whether they used the IT technologies identified in the seven IT questions on the survey. These questions regarding “use of computers” or information technology (IT) were added to the CTS Physician Survey in 2000–2001 and 2004–2005. The seven IT questions included in the 2000–2001 survey were among the nine IT-related questions included in the 2004–2005 survey, allowing for comparison of the IT-related data between these two survey rounds.

The seven Yes/No EHR IT-related questions on the 2000–2001 and 2004–2005 surveys are as follows:

1. Computers used for treatment guidelines [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information about treatment alternatives or recommended guidelines?
2. Computers used for formularies [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to obtain information on formularies?
3. Computers used for preventive service reminders [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to generate reminders for you about preventive services?
4. Computers used for patient notes or medication lists [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to access patient notes, medication lists, or problem lists?

5. Computers used for writing prescriptions [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to write prescriptions?
6. Computers used for exchanging data with other physicians [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used for clinical data and image exchanges with other physicians?
7. Computers used for e-mail with patients [2000–2001 and 2004–2005]. In your (main) practice, are computers or other forms of information technology used to communicate about clinical issues with patients by e-mail?

The outcome measure, “IT Adoption Score,” totals the number of “yes” answers to the above questions for each physician taking the surveys, yielding an IT Adoption Score for each physician of an integer between 0–7. Mean scores for groups of physicians or practices are numeric answers carried out to two decimal places between 0–7. The interest in the IT Adoption Score is to examine the association of “adoption” with various physician and practice characteristics as reflected in the independent variables. The seven IT capabilities were evaluated for scalability using Exploratory Factor Analysis, Guttman scaling, and Cronbach’s alpha techniques—analyses which revealed no factors, categories, or scaling among the seven IT items. The combinations of functionality used by the physicians in this dataset also did not follow a pattern, show associations with one another, or occur in consistent groupings. So the outcome variable IT Adoption Score is comprised of a continuous variable from 1–7 consisting of adding the total “yes” answers to the IT-related questions in any combination per physician and practice.

Independent variables: This study analyzes the IT Adoption Score according to several independent variables reflecting Physician Characteristics including gender (female); year began practice; primary care vs. specialist; career satisfaction; and race. Independent variables reflecting Practice Characteristics include: practice size (small vs. medium/large); practice ownership; and fiscal features percent of practice revenues from Medicare, Medicaid, and Managed Care sources. A description of each independent variable follows.

Physician Characteristics:

*Gender (female)*: physician gender, female or male; female is the referent category.

*Year began practicing medicine (yrbgnx)*: this variable is divided into 8 categories:

1996+ (referent): 1992–1995; 1986–1990; 1982–1985; 1976–1980; 1971–1975;  
1966–1970; and 1965 or earlier.

*Primary care or specialist (pcpflag)*: this variable identifies whether the physician is a primary care physician (family practice, general practitioner, pediatrician, other) or specialist (specialist or sub-specialist).

*Career satisfaction (careersat)*: this variable identifies whether the physician is satisfied (very satisfied, somewhat satisfied) or dissatisfied (very dissatisfied, somewhat dissatisfied) with her or his career.

*Race (race)*: this variable identifies whether the physician is non-Caucasian or Caucasian, as the categories were collapsed because 78.8% of the samples were white.



*Physician practice ownership (owner)*: this variable identifies whether the physician is an owner of the practice (full owner or partial owner) or not an owner. Ownership could be full or part-owner, and categories were collapsed into Owner and Not Owner.

Practice Fiscal Characteristics:

*Percentage revenue from Medicare (% Rev. MCARE)*: this variable identifies the percentage of revenues for the practice from Medicare.

*Percentage revenue from Medicaid (% Rev. MCAID)*: this variable identifies the percentage of revenues for the practice from Medicare.

*Percentage revenue from managed care (% Rev. MC)*: this variable identifies the percentage of revenues for the practice from managed care.

Panel Study Sample Construction:

Panel sample preparation progressed through phases of cleaning and preparing the data for analysis, then understanding the basic characteristics of the panel and practices involved. After the datasets were cleaned, restricted data sets for each round (2000–2001 and 2004–2005) were prepared. These restricted datasets for the base and second periods were then merged into a panel dataset for the analysis. Missing data were removed from the panel dataset. Several values change for the same data element for a physician between baseline and second periods: a few (i.e., four) for “gender”, a few (i.e., five) for “year graduated from medical school” (used as the basis of calculating “year began practicing”), “geography”, which has 319 of 4428 locations change between the 2000–2001 and 2004–2005 surveys, and “practice size,” with 120 changes between baseline and second periods. Physicians who changed geography from 2000–2001 and

2004–2005 were removed from the sample, and the data were checked for other anomalies. The dataset was also restricted to only those practices that are office-based, eliminating university-based and employee practices.

Constructing the panel for this analysis consisted of first creating then merging restricted datasets from the 2000–2001 (baseline period) and 2004–2005 (second period) CTS Physician Surveys. Each restricted dataset was set up using “Setup\_RestrictedData\_2000–2001” and “Setup\_RestrictedData\_2004–2005.” STATA Setup (Do File) for ICPSR 03820 (2000–2001) and ICPSR 04584 – 0002 – Setup.do were run using CTS Physician Survey data dictionaries for each respective round. Datasets were thus formed for Restricted 2000–2001 and Restricted 2004–2005.

Next, the Restricted 2000–2001 and Restricted 2004–2005 datasets were merged using the programs in “Merging Restricted\_2000–2005\_Datasets” do file. The data element in Round 4 in the 2004–2005 dataset identifying the physicians who also participated in Round 3 in 2000–2001 (thus comprising the panel) is “Value for PHYSIDX in Round 3” (R3PHYSIDX). The term “y5” was added to each variable used from the 2004–2005 dataset to differentiate the variable for the same physician in both datasets once the datasets were merged into the panel.

(A variable was created = = 2004 in save temp2.dta CID Use temp2. The code to drop if CID = 0 was invoked since that physician is not relevant if there is no R3PHYSIDX for that physician ID).

One record per physician in the panel was created. Small variations in the data for the same physician between 2000–2001 and 2004–2005 were identified, such as for the variable “year graduated from medical school” (i.e., five physicians changed responses), numbers minor

enough to not affect results in a meaningful way. The baseline survey 2000–2001 was used as the reference variable for each variable in the panel. Then any missing records (if they were zero) as well as any outside the range of possible values were dropped. A new variable was created to match on the both variables called “y5var”.

The restricted data sets for 2000–2001 and 2004–2005 were then merged to create the panel for this analysis. The STATA setup (DoFile) was first run for the baseline 2000–2001 dataset (ICPSR 03820), then for the second period 2004–2005 dataset (ICPSR 04584). The output was saved under BALGRO Restricted Data (Originals) and Restricted Data (Final). Datasets were formed for Restricted 2000–2001 and Restricted 2004–2005.

Next, Restricted Datasets 2000–2001 and 2004–2005 were merged using

“Merging\_Restricted\_2004–2005\_Datasets” do file. R3PHYSIDX = Round 3 physician id number inside 2004-5 dataset.

“y5” was added to each variable in 2004–2005 dataset to be able to differentiate that variable for the same physician when the panel is merged. Four thousand, four hundred, twenty-eight (4,428) of the physician identifier (PHYSIDX) variables overlapped in the merged datasets.

Since data from the 2000–2001 dataset is used as reference when appropriate, geography was next tested for the level of change between 2000–2001 and 2004–2005. To test geography change, “assert SiteID = y5SITEID” resulted in 319 physicians of the total panel of 4428 with a changed geographical location from 2000–2001 to 2004–2005. This was interpreted as meaning out of the 60 sites, 319 moved from their 2000–2001 location and filled out the 2004–2005 survey anyway. The panel dataset was further restricted to not include the physicians whose practice size changed plus or minus ten physicians from the base year (2000–2001) to second

period (2004–2005). “Practice size” changed by ten or more, for one hundred-twenty (120) physicians from base to second periods, and so these respondents were eliminated from the sample.

The sample was restricted to office-based physicians, eliminating employed and government physicians. This was done so results would be generalizable to the universe of office-based physician practices and associated EHR adoption characteristics, as the study aims to identify characteristics of office-based practices and physicians that have a positive or negative association on EHR adoption. The study may not appropriately generalize to physicians who are employed or working in government settings where corporate direction can be given and system decisions made collectively or corporately vs. independently as in office practices. After analyzing whether the combination of “Ownership” and “Employment” data elements, or “All Practice Types” and “Setting” data elements were preferable to use in creating the sample, the combination of “All Practice Types” and “Setting” were used because they resulted in the sample more reflective of the population to which the study questions can be generalized, i.e., office-based physician practices. Thus the data elements used to create the panel sample include “ALLPRTP = All practice type” and “SETTING = Setting where spend most time”.

The net Panel Sample consists of 3,164 respondents. For the descriptive statistics for the data elements with no or minor differences in the panel data between the two time periods, the 2000–2001 values are used. For example, the number of differences for the same physician between the 2000–2001 and 2004–2005 samples for “gender” is four and for “year began practice” is five. These are not considered meaningful differences, so the 2000–2001 values for gender and “year began practice” are used.

## Creating Variables

Practice size was divided into “Small” and “Medium/Large.” Practice size was considered “Small” if the number of physicians in the practice is 1–4 physicians; “Medium/Large” was defined as 5 or more physicians in the practice. So in the code, small = 1 = 1–4 physicians, and medium/large = 0 = >4 physicians.

A dummy variable was created for “gender”, using “Female” as referent since the majority of participating physicians were Male (i.e., 75%). Four respondents changed “gender” answers between 2000–2001 and 2004–2005, so the base year (2000–2001) “gender” values for those four physicians were used for the descriptive statistics for the panel, assuming the same across both rounds. In the code, gen gender female = 1.

A categorical variable (YRBGNC) was created for “year began practicing medicine” (YRBGNPRAC), beginning with “1996+” and ending with “before 1965,” creating categories in four-year progressive increments from that baseline. This was then used to verify whether “year began practicing medicine” matched for the same physician between the two rounds (i.e., YRBGNPRAC matched y5YRPGNPRAC). The referent category for this variable is 1996+, with other categories as follows: 2 = 1991–1995, 3 = 1986–1990, 4 = 1981–1985, 5 = 1976–1980, 6 = 1971–1975, 7 = 1966–1970, and 8 = 1965 or earlier.

Next, “specialty” was identified and physicians were categorized as “primary” or “specialist.” To identify primary care physicians (PCP), the data element PCPFLAG (present in both the baseline and second surveys) was used and the variable “pcpflag” was coded using that data element. The data element SPECX identified specialists in both 2000–2001 and 2004–2005 datasets. For descriptive statistics, the base year (2000–2001) value was used for primary care vs. specialist

identification for each respondent. For “specialty,” fifty-seven (57) primary care physicians and twenty-seven (27) specialists shifted from base to second periods.

More movement between base and second periods occurred in the career satisfaction data elements. The original ordinal career satisfaction variable was measured on an ordinal 1-5 scale – this was dichotomized into “career sat” if the variable was 4–5 or “career dissat” if the variable value was 1, 2, or 3. Career dissatisfaction included “neither satisfied nor dissatisfied” (3), in addition to “dissatisfied” (2) and “very dissatisfied” (1) on the original scale. Career satisfaction for the base year was labeled “carsatb.” Similarly, “y5carsatb” was defined as the career satisfaction variable for the second period (2004–2005). The panel career satisfaction variable was created by first generating four categories (0, 1, 2, 3), with Category 0 = satisfied base period and satisfied second period; Category 1 = satisfied base period and dissatisfied second period; Category 2 = dissatisfied base period and satisfied second period; and Category 4 = dissatisfied base period and dissatisfied second period. A second variable “carsatd” was included in the analysis to indicate whether there was a change in satisfaction between the base and second periods. Thus, dichotomous variables “carsatb” and “carsatd” were created to measure the change (delta) in career satisfaction between base and second periods. Since most of the sample was satisfied in both periods—i.e., 10+% dissatisfied both periods, and 10% dissatisfied base or second period—two variables were coded representing: “not satisfied base”/“not satisfied second period, and “satisfied base” and “satisfied second period”. Career satisfaction (CARSAT) for base period (2000–2001) was used as the referent.

For race, the RACE variable in the surveys was used, and a “non-white” dichotomous variable was created, since the majority (80.53%) of participating physicians were white. Forty-five (45)

physician respondents answered, “don’t know” (d) or “refuse” (r) for RACE in the surveys.

These were coded as non-white and included in those numbers.

For practice ownership status the surveys’ TOPOWN variables (“type of practice owners”) were used. The referent was “owner in both periods” 2000–2001 and 2004–2005 (Owner = 0). For the ownership variable, four categories were created: 0 = “owner base period and second period”; 1 = “owner neither base nor second periods”; 2 = “owner base period and not second period”; and 3 = “owner second period and not base period.”

Next the dataset was scrutinized to determine what other variables might be needed for the analysis. Panel sample variables were examined for baseline (2000–2001) and second (2004–2005) periods. Exploratory regression analyses were run with base period data to see what results were of interest. Cross-tabulations were run on variables for baseline and second periods to look for meaningful changes between rounds, and consider whether potential relationships of interest might be present between those changes to IT Adoption Scores for the analysis.

Panel sample statistics were compared to the descriptive statistics for the pooled dataset used in Chapter 4 Analysis (Difference-in-Differences) to determine which data elements should be used from the baseline period as the descriptive value for independent variables. Functionality changes between the two rounds were examined including: cross-tabs of the IT Adoption Score for 2000–2001 by 2004–2005 average IT Adoption Scores, estimates of changes in IT Adoption Scores, interaction of IT Adoption Scores with key physician and practice characteristics, and recasting the outcomes variable as three outcomes (reduced, added, or retained) IT functionality.

Preparing to analyze changes in IT Adoption, variables were constructed reflecting total IT Adoption Scores as a measure of each physician's total use of the seven IT functionalities for each of the two rounds:

```
egen byte
```

```
total_it=rsum(IT_TRT*IT_FORM*ITRMNDR*ITPRESC*ITNOTES*ITCLIN*ITCOMM)
```

and

```
egen byte
```

```
y5total_it=rsum(IT_TRT*IT_FORM*ITRMNDR*ITPRESC*ITNOTES*ITCLIN*ITCOMM)
```

From this total IT Adoption Score, a difference variable was created: `gen byte`

```
dtotal_it=y5total_it - total_it.
```

A compression variable was created (-1 0 +1) to make the analysis output cleaner for presentation in Table 5-4: Changes in IT Adoption Scores among physician practices: addition, retention, or reduction of EHR functionality among panel physicians 2000–2001 to 2004–2005.

Dummy variables for independent variables were prepared for the analysis to look for relationships between their values and significant associations with changes upwards or downwards in IT Adoption Scores. These include gender (female referent), primary vs. specialty (primary care referent), career satisfaction (satisfied referent), race (non-white referent), practice ownership (owner neither referent), percent revenue from Medicare, percent revenue from Medicaid, and percent revenue from Managed Care. The ownership variable was chosen over the salaried/non-salaried variable, as a more accurate way to see if the physician's payment structure influenced adoption, and whether being an owner or non-owner in the practice in the base year vs. the second period was associated with IT adoption. For ownership, four categories were



created and examined: owner both periods, owner neither period, owner the first period but not the second, and owner the second period but not the first. In calculating this statistic the TOPOWN (“type of practice owners”) variable was used; then the change in IT Adoption Score associated with each condition was estimated.

In preparing the variables for percentages of Medicare, Medicaid, and Managed Care revenues, the continuous variable REV was defined to enable examination of changes upward, downward, or stasis in IT adoption in relationship to levels of Medicaid revenues (PMCare = % revenues from Medicare, PMCaid = % revenues from Medicaid, and PMC = % revenues from Managed Care). These variables were also used to evaluate change in IT Adoption Score comparing baseline (2000–2001) to second period (2004–2005) percentages of practice revenues associated with Medicare, Medicaid, and Managed Care.

### **Data Analysis and Results:**

Descriptive statistics for the panel were created for the baseline (2000-2001) and second (2004-2005) periods and presented in Table 5-1: Descriptive Statistics of Physician Panel 2000-2001 – 2004-2005. Each EHR functionality was analyzed for base rate, retained, dropped, added, or non-usage and presented in Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians 2000–2001 – 2004–2005 Full Panel Sample. Regression of the average change in Total IT Adoption Score was estimated for the full panel, for small practices, and medium/large practices to evaluate the association between IT Adoption Score and physician and practices characteristics represented in the independent variables. Results of this regression are presented in Table 5-3: Trends in averages in physician use of EHRs by full panel sample, small, and medium/large practices among panel over time (2000–2001 – 2004–2005). Cross-tabs for

baseline and second period IT Adoption Scores for the Full Panel, the Small Practice Sample, and the Medium/Large Sample were reviewed to identify notable occurrences or themes in increases, retentions, or reductions in IT functionality usage.

Next, evidence of additions, reductions, and retentions in usage of EHR functionality was evaluated according to size of practice. In the difference-in-differences (DID) analysis in Chapter 4 of this dissertation, the gap in the difference in EHR adoption by Small vs. Medium/Large practices as measured by the IT Adoption Score variable widened over the period 2000–2001 to 2004–2005. In the Chapter 5 panel analysis, the change in total IT Adoption Score for the base period (2000–2001) compared with the second period (2004–2005) was evaluated across practice and physician characteristics. This change in total IT Adoption Score was then interacted with size of practice and the change in the IT Adoption score per physician practice, regardless of where they started with the IT Adoption score.

This suggested the need to set up variables regarding changes in adoption from the base period to second period (increases, decreases, and retentions), i.e., which physicians in practices with which characteristics increased functionality, gave up functionality, or stayed the same, examining for evidence of drivers in all three cases. To focus on trends in EHR adoption among practices and physicians, changes in adoption for each of the seven IT functionalities were examined over the panel time horizon to identify prominent shifts or themes in EHR functionality usage. Trends in IT adoption were analyzed by size of practice (i.e., Small vs. Medium/Large) to evaluate the differences in adoption between these two categories of practices. A measure of interaction was constructed to allow a stratified analysis comparing Small to Medium/Large practices. Changes in IT Adoption Scores were analyzed to discern direction of changes in IT functionality use, i.e., to examine how much functionality was added, retained, or

de-adopted among the total panel, then among members of small practices and medium/large practices. The interaction between variables for the Small and Medium/Large practices, and physician and practice characteristics was assessed for association of each characteristic with changes in IT adoption.

The composite IT Adoption Score calculated for the descriptive statistics was examined for potential influence of independent variables reflecting physician or practice characteristics to identify which would be important to report or analyze further.

### Results:

As presented in Table 5-1, in the full panel sample (N = 3,164), the IT Adoption Score increased from 1.97 to 2.57, an increase of 0.6 from the base period (2000–2001) to the second period (2004–2005). Practice Characteristics: the majority of practices in the full panel sample were Small Practices in the base and second periods, 1739 (54.96%) and 1,812 (57.27%), respectively. The majority of physician respondents, 2,064 (65.23%), were owners in their practices both baseline and second periods. Percentage of revenue for the practices in this sample remained about the same for Medicare (about 30%), Medicaid increased 0.5% (from 12.80% to 13.13%), and Managed Care sources decreased 2.33% (from 46.37% to 43.94%) between baseline and second periods. Physician characteristics include female physicians were in the minority (23.36%), career satisfaction was virtually unchanged on average (approximately equal numbers became dissatisfied or satisfied between the two periods), and non-white physicians (19.47%) were a distinct minority of this sample.

IT functionalities most-to-least commonly used in both periods, as reflected in “Retained” in Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians 2000–

2001 – 2004–2005 Full Panel Sample include, in descending order: “Use of IT to get information on guidelines and treatment alternatives” (IT\_TRT) (40.17%); “Exchanges data with other physicians” (ITCLIN) (23.01%); “Uses IT to access patient notes or medication lists (ITNOTES) (22.85%); “Uses IT to obtain information on formularies” (IT\_Form) (17.38%); “Uses IT to generate reminders for preventive services” (ITRMNDR) (14.03%); “Uses IT to communicate with patients regarding clinical issues” (ITCOMM) (10.81%); and “Uses IT to write prescriptions” (ITPRESC) (6.29%). While use of all seven IT functionalities had a net increase in the panel sample, the greatest net change from the base to second periods (considering IT functionality retention, reductions, and additions) occurred in “Uses IT to obtain information on formularies,” with a net increase of 14.26%. “Use of IT to get information on guidelines and treatment alternatives,” “Uses IT to access patient notes or medication lists,” and “Uses IT to write prescriptions” each increased in net use about 10%, and “Exchanges data with other physicians,” “Uses IT to generate reminders for preventive services,” and “Uses IT to communicate with patients regarding clinical issues” each increased net use about 5% between base and second periods. Overall, for those all IT functionalities dropped at about 10% except “Uses IT to write prescriptions” (ITPRESC) which dropped 4.05%; and IT functionalities were added at least at 11.76% for “Uses IT to communicate with patients regarding clinical issues” (ITCOMM) up to 23.29% for “Uses IT to obtain information on formularies” (IT\_Form). Percentages of dropped functionality occurred among use of all seven IT functionalities—about one-half as many were dropped as added between the base and second periods.

Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians 2000–2001 to 2004–2005. Changes in IT Adoption Scores from 2000–2001 to 2004–2005 were analyzed by examining changes for *each* of the EHR IT-related variables: IT\_TRT (use of

computerized treatment guidelines), IT\_FORM (use of computer prompted formularies), ITRMNR (use of computerized preventive services reminders), ITNOTES (documenting patient notes or medication lists using the computer), ITPRESC (ordering prescriptions with the EHR), ITCLIN (exchanging data with other physicians for care of the patient), and ITCOMM (emailing with patients); changes examined were IT functionalities *retained*, *added*, or *dropped* over the course of the panel time period. Results are reflected in Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians 2000–2001 to 2004–2005 from crosstabs for baseline period vs. the second period for each variable. The data presented in this table reflects baseline counts of each IT function data element, plus additions, reductions, and retentions from base to second periods.

As presented in Chapter 4 of this dissertation, no particular pattern or scale emerged from the data regarding combinations of IT functions that were implemented in groups or sequences. The most frequently added IT functions among the panel are “Computers used for formularies” (IT\_Form) (23.29%), “Computers used for treatment guidelines” (IT\_TRT) (21.59%), and “Computers used for exchanging clinical data and images with other physicians” (ITCLIN) (19.06%). The most frequently de-adopted IT functions were “Computers used for exchanging clinical data and images with other physicians” (ITCLIN) (12.33%), “Computers used for treatment guidelines” (IT\_TRT) (11.13%), and “Computers used for preventive service reminders” (ITRMDR) (10.08%).

Table 5-3: Regression analysis was performed to estimate important statistics reflecting averages in IT Adoption Scores over time between small and medium/large practices and these results are presented in Table 5-3: Trends in averages in use of EHR among small and medium/large

physician practices among panel over time (2000–2001 to 2004–2005). Interpretation of regression results with Confidence Intervals.

Table 5-3: Trends in averages in use of electronic health records (EHR) among small and medium/large physician practices among panel over time (2000–2001 to 2004–2005) presents results of regression analyses for Full Sample with Practice Size Dummy, Small Practice Size Sample, and Medium/Large Practice Size Sample, estimating the impact of independent variables within different practice sizes on IT adoption scores. This table reports estimates of change in IT Adoption scores testing whether the coefficients explain enough variance in IT Adoption Scores to be statistically significant. These results are presented as three tables side-by-side: for all practices (regression for Full-panel Sample with Pracsiz Dummy), Small Practices (Small Pracsiz Sample==1), and Medium/Large Practices (Large Practice==0).

For the Full Sample, mean scores for IT Adoption were significantly higher in those practices with physicians who began practice between 1981–1985 ( $p<0.05$ ), those in primary care practices ( $p<0.01$ ), and significantly lower for non-white physicians ( $p<0.05$ ) and for small practices ( $p<0.001$ ). Regression estimates presented in Table 5-3 for Small Practice Size, include significantly higher mean scores for IT Adoption Scores for physicians beginning practice between 1991–1995 ( $p<0.05$ ) and 1981–1985 ( $p<0.05$ ), and for those physicians who were owners neither base or second periods ( $p<0.05$ ), and significantly lower mean IT Adoption Scores for non-white physicians ( $p<0.05$ ). Also presented in Table 5-3, regression estimates for the Medium/Large Practice Size sample indicate that none of the independent variables significantly influenced Medium/Large Practice mean IT Adoption Scores.

Tables 5-4, 4a, 4b, and 4c: Changes in IT Adoption Scores among all practices: addition, retention, or reduction of EHR functionality among panel physicians 2000–2001 – 2004–2005, present changes in use of IT functionalities (additions, reductions, and retentions) between base and second periods for the Full Practice Sample, Small Practice Sample, and Medium/Large Sample, respectively.

Table 5-4 results for the Full Panel Sample show that additions, retentions, and reductions in IT functionalities are not concentrated in any one size of physician practice – rather they occur in Full, Small Practice, and Medium/Large Practice samples, with some variability in frequency.

Tables 5-4a and 5-4b results show Small Practices within the panel are slightly less likely than Medium/Large Practices to have adopted IT functionality at the beginning and ending points of the panel distribution (IT Adoption scores of zero (0) were 31% baseline and 24% second period for Small vs. 20% baseline and 11% second period for Medium/Large Practices). Small practices experienced about one-half the drop in the lower IT Adoption Scores (0/0, 1/1, 2/2) as Medium/Large practices (-5% vs. 10%; -5% vs. -7%, and +1% vs. -2%, respectively). While the gains for Small vs. Medium/Large Practices in the middle range of IT Adoption scores (3, 4, 5) were similar, Medium/Large practices had greater gains in IT Adoption than the Small Practices at the high end (6, 7) of the distribution of adds/drops (consistent with a larger drop in lower scores). At the high end of the distribution (IT Adoption Scores of 7), scores increased only 40% (from 1.15% to 1.61%) for Small Practices while Medium/Large Practice IT Adoption Scores of 7 increased by about 250% (from 2.67 to 6.8%) from base to second periods. Even though there were fewer Medium/Large Practices (1,739 Small vs. 1,425 Medium/Large), this resulted in the Full Sample IT Adoption Scores increasing overall - the drop in “0” IT Adoption Scores was about one-fifth (from 30.76% to 24.44%) for the Small Practice Sample vs. a drop of about half

(20.14% to 10.95%) for Medium/Large Practices. Zero/zero (0, 0) scores for the Full Panel = 25.98; for Small Practice Sample = 30.76, and Medium/Large Practices = 20.14 reflect overall lower levels of IT Adoption for Small Practices. Even though Small Practices experienced increases overall, their improvement was lesser, and they fell further behind the Medium/Large Practices between the base and second periods. (This is consistent with results of the difference-in-differences analysis (DID) of Chapter 4.)

Table 5-4c: Specific changes in IT adoption scores (increased, reduced, and retained use of EHR functionalities) are presented in Table 5-4c. Of 3,164 physicians in the Full Panel, 47.7% (1,336) increased their use of IT functionality; 30% (948) retained equivalent numbers of adopted IT functions, and about 22% (706) of the Full Panel de-adopted or reduced the number of IT functions used in their practices. For the Full Sample, almost three-fourths (72%) as many respondents reduced as increased the number of IT functionalities used.

Results presented in Table 5-4c show Small Practices are less likely than Medium/Large Practices to add IT functionality (42.6% vs. 54%), and slightly more likely to reduce or de-adopt functionality (23.9% vs. 20.4%), with the net effect of Small Practices having a larger proportion than Medium/Large Practices with the same IT Adoption Scores in the second period as the baseline (33.5% vs. 25.6%) respectively. For the Small Practice Sample, slightly over half (56.5%) as many respondents reduced as increased the number of IT functionalities used. For the Medium/Large Sample, fewer than half (43%) as many respondents reduced as increased the number of IT functionalities used.

Table 5-5: Linear regression model of change in total IT Adoption Score for full panel and stratified by practice size (Small and Medium/Large Practices) presents regression results for



“Change in IT Adoption Score” for Full Panel, Small Practices, and Medium/Large Practices, estimating associations between physician and practice characteristics and changes in IT adoptions scores for Small and Medium/Large practices. Estimates of changes in IT Adoption Scores for the Full Panel Sample, Small practices, and Medium/Large practices were interacted with key independent variables reflecting physician and practice characteristics *including* baseline IT Adoption Scores to understand the influence of the starting point on estimations of the effect of independent variables on the change in EHR adoption (as measured by change in IT Adoption Score). Inclusion of the baseline IT Adoption Score in the regression helps explain the change in IT Adoption Scores in relative terms, allowing the influence of the starting point on the total change to be taken into consideration, i.e., the higher the baseline IT Adoption Score the respondent starts with, the smaller a change in score is possible.

Overall, for the Full Panel Sample, mean scores for IT Adoption were significantly lower on average for physicians who are female ( $p<0.05$ ), in the oldest group ( $p<0.05$ ), non-white ( $p<0.05$ ), owner in neither base nor second periods ( $p<0.05$ ), or in small practices ( $p<0.001$ ). Mean scores for IT adoption were significantly higher for physicians who are: owner neither period ( $p<0.05$ ).

The regression for the Small Practice Size sample shows that IT Adoption Scores are lower on average for physicians who are female (not significant,  $p<0.05$ ), and significantly lower for the oldest physician category ( $p<0.05$ ), non-white ( $p<0.05$ ), and owner neither period ( $p<0.01$ ) within *small* practices. These results show the smaller practices are more sensitive to physician characteristics—which effects are muted in Medium/Large practices. The only independent variable coefficient in Medium/Large practices that significantly influences IT Adoption is “percentage of revenues from managed care” ( $p<0.05$ ). R-squared for this regression is 0.1845.

Table 5-6: IT Adoption among panel physicians and interaction with physician and practice characteristics for 2000–2001, 2004–2005, and Full Panel. This table presents regression estimates and estimate of change in IT Adoption Score interacted with key physician and practice characteristics in the baseline period (2000–2001), second period (2004–2005), and for the Full Panel (2000–2005).

IT adoption among panel physicians was most strongly associated with the following physician and practice characteristics: Results of this analysis show that in the baseline period (2000–2001) physician and practice characteristics associated with *less* likelihood of adopting EHR functionalities include: female ( $p<0.001$ ), oldest physician group ( $p<0.001$ ), primary care physician ( $p<0.001$ ), and being part of a small practice ( $p<0.001$ ). In the baseline period, characteristics associated with being *more* likely to adopt IT include: owner neither period ( $p<0.01$ ), owner baseline period ( $p<0.01$ ), and revenue from managed care ( $p<0.001$ ). R-squared for this regression is 0.0649.

In the second period (2004–2005), physician and practice characteristics associated with being *less* likely to adopt IT include: female ( $p<0.001$ ), oldest and next-to-oldest physician groups ( $p<0.001$  and  $p<0.01$ , respectively), and being part of a small practice ( $p<0.001$ ). Characteristics in the second period (2004–2005) associated with being *more* likely to adopt IT include: owner neither period ( $p<0.001$ ), owner base period only ( $p<0.01$ ), owner second period only ( $p<0.05$ ), and revenue from Managed Care ( $p<0.001$ ). R-squared for this regression is 0.1039.

For changes in IT adoption from baseline to second periods for the Full Panel, characteristics associated with being *less* likely to adopt IT include: non-white ( $p<0.01$ ), and part of a small practice ( $p<0.001$ ). Characteristics associated with being *more* likely to adopt IT include: starting

practice in 1981–1985 ( $p < 0.05$ ) and primary care physician ( $p < 0.01$ ). R-squared for this regression is 0.0233.

## **Discussion**

### De-adoption:

Significant reduction in IT Adoption Scores, or *de-adoption*, occurs in the panel over the six-year time period. De-adoption is prominent in the panel between the baseline and second periods in both Small and Medium/Large Practices. While IT Adoption scores increase overall and the range of adopted IT capabilities grow over time, a significant number of physician practices reduce functionality over time. Since overall EHR adoption within the panel grows over time, what remains largely hidden if only adoption rates are tracked is the significant number of capabilities de-adopted by physician practices over a time period. These de-adopted IT functionalities, i.e., IT capabilities that physicians have previously adopted then drop rather than retain, are muted by net increases in IT adoption scores on average across the small and medium/large practice size groups over the same period of time. This was a surprising result, as studies in the literature largely only report gains in or barriers to adoption of EHR functionality (DesRoches C. M., 2015) (DesRoches C. , et al., 2008) (Office of the National Coordinator, 2010). These “progress reports in adoption of EHRs” leave the impression that all movement is upwards or static in IT Adoption when only relative rates of upward adoption movement are reported. For this study, reductions of functionality in such numbers were not expected; rather the focus of the study was initially on the characteristics associated with adoption IT functionality. The sizable rates of de-adoption among members of the Full panel, Small Practice, and Medium/Large Practice samples as the data reveal were unexpected based on “adoption

only” oriented literature, and this is a noteworthy finding (Jamoom, Beatty, Bercovitz, Woodwell, Palso, & Rechtsteiner, 2012).

This finding contrasts currently available literature, which seemingly only speaks to adoption or barriers to adoption, not *de-adoption* (Burt, 2005) (Andrews, Pearch, Ireson, & Love, 2004) (DesRoches C. M., 2015) (Burke-Bebee, 2008) (DesRoches C. , et al., 2008) (Jamoom, Beatty, Bercovitz, Woodwell, Palso, & Rechtsteiner, 2012). The implication of this tendency in the literature is that researchers might assume, as inferred in the current body of literature that once an IT functionality is adopted, that it is retained – clearly this dissertation study result says this is a fallacious assumption. The IOM Report “Patient Safety and HIT: Unintended Consequences” calls out the paucity of good research in EHR and health information technology adoption) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

This evidence of de-adoption points out that on an ongoing basis in physician practices, special attention and vigilance should be paid to retention of functionality that has been adopted during an EHR system implementation through sustained support and training efforts. Care should be taken by consultants and vendors to not simply focus implementation methodologies and project plans based only on introducing new functionality in organizations, but should also focus on maintaining user engagement and training, and monitoring continuation in use of already existing functionality. This suggests enhancing methodologies for implementing and supporting EHRs, to continuously test to make sure those capabilities that have been implemented and adopted are retained. This would assure that adding new functionality to that base is able to take advantage of already existing foundational functionality, creating a more comprehensive, safer system. This concept is consistent with marketing principles that state that to grow market share, it is important to not just add new customers, but keep existing ones as well (Jao, 2015). Clearly,

if de-adoption is occurring in EHR implementations, the practices paying for these expensive systems and resources necessary to implement them are not getting the “benefit of their bargain”, an important concept in negotiation of software contracts, although assigning responsibility to the de-adoption would be challenging (USLegal, 2015). Thus, physician practices could negotiate retention of functionality into their contracts with vendors, and create incentives for vendors to help these practices maintain hard-fought EHR functionality and as a practical step forward in finding ways for vendors to be held accountable to functionality working the way it is supposed to (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

The is dissertation’s de-adoption finding also suggests the possibility that certain IT functionalities are more or less important to the practices at different times. Or more likely, these IT capabilities might be de-adopted because their initially-assumed value proposition or ease of use did not pan out as expected, i.e., complaints today are rampant among physicians about ways that EHR functionalities create inefficiencies for providers in their practices, leading them to retreat to paper processes that were previously more efficient or effective for certain functions, contributing to de-adoption (Jha, et al., 2003) (HITC Staff, 2015) (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012). Since this dissertation provides evidence of the de-adoption phenomenon occurring pre-ACA and pre-ARRA/HITECH, testing for de-adoption in the post-ACA and post-ARRA-HITECH environment is important, given the large investment in EHR adoption being made by the Federal Government and evidence that significant numbers (22%) of physicians de-enrolled from Meaningful Use Stage 2 in spite of financial incentives and penalties (HITC Staff, 2015).

EHR functionality de-adoption has policy implications for Meaningful Use – while physician practices (and hospitals) are fast-tracking EHR implementations in their practices and organizations in order to participate in HITECH and obtain earned incentive payments by achieving Meaningful Use criteria, the ONC audit function that validates adoption of Stages 1, 2, and 3 of Meaningful Use should pay special attention as they measure subsequent stages (2 and 3), to re-measure earlier stages (1 and 2) and not assume that once Stage 1 is achieved, that it will be retained through Stages 2 and 3 (Blumenthal & Tavenner, 2010) (DesRoches, Audet, Painter, & Donelan, 2013). The ONC should repeat earlier stage functionality in their reporting requirements for providers participating in Stages 2 and 3, to assure continuity of adoption of EHR functionality that meets Meaningful Use criteria on an on-going basis. Given the purpose of incentive payments, this might bring up issues regarding continuing to provide the incentive CMS payment levels for Medicare patients for these providers unless they are still using the adopted Stage 1, 2, and 3 functionalities over time. Certainly, policy governing the incentive program should be evaluated with de-adoption in mind. At a minimum, ONC should require continuous reporting, and not just one-time measurement and compliance per Meaningful Use Stage.

Additional policy implications should reconsider the need for continuation of Regional Extension Center (REC) support for small, rural, and safety net providers, potentially not discontinuing these support services for small practices, rural hospitals, and safety net organizations once the MU implementation period has passed. This evidence that discontinuation of EHR adoption support, especially for small practices that struggle to adopt functionality as well as maintain it, supports the need for on-going support to not allow EHR adoption progress to erode over time. The higher level of de-adoption by small practices is one reason why they fall

further behind medium/large practices in EHR capabilities over time, despite the intentions, investment, and efforts expended as part of HITECH for physicians, the government, and other involved parties.

De-adoption of EHR functionality has implications for the government's further plans for building upon the Meaningful Use-inspired EHR base, through telemedicine and telehealth capabilities for care management and chronic care management (CCM). Several new telehealth and telemedicine codes for Chronic Care Management (CCM) have been published, with CCM code 99490 activated January 1, 2015, with plans for additional telehealth/telemedicine codes in the future (Steed, 2014) (Wicklund, CMS boosts telehealth in 2015 physician pay schedule, 2014). These telemedicine and telehealth codes consistent with Meaningful Use Stage 3 criteria reflect the government's desire to direct more care to digitally enabled vs. human-driven processes. Meaningful Use Stage 1 and Stage 2 EHR capabilities in physician practices create the foundational platform and data exchange capabilities necessary for extending telehealth and telemedicine functionalities or extensions into communities, directly connecting patients to providers (Steed, 2014) (News Staff, 2015) (Sullivan, 2015). The massive HITECH initiative is part of an overall strategic plan from the Office of the National Coordinator (ONC), in an effort to lay the IT foundation necessary to enable digital care and preventive digital health capabilities. These capabilities lay down the necessary infrastructure to enable chronic disease care and care management and coordination for value-based models such as Accountable Care Organizations (ACO) and medical homes. These new models require IT infrastructure to reduce cost, change the nexus of chronic care, and improve the quality and value of efforts and investment of practices and CMS (The Commonwealth Fund, 2009).

This dissertation's de-adoption evidence suggests federal policy designed to support HITECH and EHR infrastructure will be more expensive than previously planned in its effort implement and sustain EHR adoption. However, by investing in the maintenance of adoption, replacement of software as a means of correcting problems in EHR implementations in organizations will likely be reduced, potentially reducing overall software spend (Miller, West, Brown, Sim, & Ganchoff, The Value Of Electronic Health Records In Solo Or Small Group Practices, 2005)

This study adds to existing literature by providing evidence of addition, retention, and reduction (de-adoption) of EHR functionality among physician practices, highlighting the phenomenon of de-adoption, which is thus far not addressed in EHR and IT literature.

Small Practices lag further behind Medium/Large Practices in IT Adoption over time:

Small Practices fell further behind Medium/Large Practices in IT Adoption over time, a finding that supports the study's hypothesis: *Small-size physician practices (four or fewer physicians) will adopt fewer EHR capabilities than medium/large practices (five+ physicians).*

Study results provide evidence that Small Practices fell further behind Medium/Large Practices in IT adoption from the baseline to second period. While IT adoption for both Small and Medium/Large practices increased, Medium/Large Practices increased at a greater rate; small practices increased at lower rates. Overall, small practices lost ground on average, controlling for independent variables and in the context of the overall healthcare environment. Small Practices were about one-half point behind Medium/Large Practices on average IT Adoption score in the base period, and one-point behind in second period compared to medium/larger practices, even as they adopted EHR functionality. For each increase of one unit in IT Adoption Score for Medium/Large Practices in the base period, the average change in mean IT Adoption Score for



Small Practices was less by 0.52 ( $p < 0.001$ ). For each increase of one unit in IT Adoption Score for Medium/Large Practices in the second period, the average change in mean IT Adoption Score for Small Practices was less by 0.94 ( $p < 0.001$ ). (Table 5-6)

This finding is underscored by results presented in Table 5-4, which show that among the Small vs. Medium/Large Practices, respective drops in Total IT Score of zero (0) for Small vs. Medium/Large Practices were 6% and 10%, respectively. For zero (0) IT Adoption Scores in both periods, Small Practices went from 30.76% zero (0) baseline scores to 24.44% in the second period; this contrasts with a larger drop in zero (0) scores for Medium/Large practices, which fell from 20.14% to 10.95%, about 10%. This greater reduction in zero scores by the Medium/Large Practices reflects a widening gap in IT adoption between the Small and Medium/Large Practices due to the greater rate of increase in IT Adoption Scores by Medium/Large Practices over time.

Changes in IT Adoption Scores from baseline to second periods at the upper IT Adoption Scores (5, 6, and 7) also reflect the lag of the Small Practices behind Medium/Large Practices. For IT Adoption Scores of 7 (the highest score) in both periods, Small Practices started at 1.15% at the baseline and increased to 1.61% in the second period, while Medium/Large Practices increased from 2.67% at baseline to 6.88% for the second period. This increase reflects a 50% increase in “7” scores for Small Practices, compared to an approximately 250% increase for Medium/Large Practices for the highest IT Adoption score.

For the Full Panel Sample, almost one-half (47%) as many respondents reduced as increased the number of IT functionalities used. This result further qualifies the hypothesis that IT adoption would increase for the entire panel, absorbing Small Practices’ lower adoption rates over time within the larger increase in IT Adoption in the Full Panel. While the overall adoption rate

increased, the gap in IT Adoption widened further over time between Small and Medium/Large Practices.

For the Small Practice Sample (1,739 physicians), about 45% (777) increased their use of IT functionality; and about 22% (379) of the panel reduced or de-adopted the numbers of IT functionalities used in their practices for patient care purposes. For the Small Practice Sample, about half (49%) as many respondents reduced as increased the number of EHR functionalities used.

In the Medium/Large Practice Sample (1,425 physicians), about 57% (818) increased their use of IT functionality; about 26% (365) retained equivalent numbers of adopted IT functions, and about 17% (242) of the panel reduced or de-adopted the numbers of EHR functionalities used in their practices for patient care purposes. For the Medium/Large Practice Sample, about 30% as many de-adopted as increased IT functionalities between base and second periods. This evidence of greater de-adoption for Small vs. Medium/Large Practices is an additional indication of lesser adoption of EHR functionality by Small Practices.

For the Full Panel Sample, about 47% as many respondents reduced as increased the number of IT functionalities used. Results reflect a greater proportion of reductions within the Small Sample, and a greater proportion of increases in the Medium/Large Practice Sample – results diluted when looking at just the Full Panel Sample.

This led to an examination of the data to identify physician and practice characteristics associated with increases and decreases in adoption, in particular the differences in these associations depending on practice size. Changes in IT adoption scores among Small vs. Medium/Large Practices reveal that IT Adoption in Small Practices is more greatly influenced by

individual physician characteristics such as gender, race, age, and ownership, while the effects of individual physician characteristics are muffled in Medium/Large Practices due to greater numbers of physicians, and possibly infrastructure and resources of the larger practices to support IT implementation and adoption. This supports the Hypothesis: *In the overall context of the regulatory, reimbursement, and other environmental conditions, predictors or drivers associated with physician adoption of EHR functionalities will be different in Small Practices than Medium/Large Practices.* Results of this dissertation indicate predictors or drivers of EHR adoption among Small Practices vary from those associated with EHR adoption among Medium/Large Practices.

These differences provide evidence that lower adoption of EHR functionalities by Small Practices is driven by individual physician characteristics in the context of their overall environment, and as such, this lower adoption persists over time. Small Practices adopt at lower rates than Medium/Large Practices, as well as de-adopt at higher rates (22% small vs. 17%, respectively), supporting the hypothesis of this study: *the gap in IT Adoption between Small and Medium/Large Practices widens over time.*

The net effect of these findings is that Small Practices are disadvantaged in accessing the efficiencies, quality improvements, and financial incentives associated with EHR adoption (Burke-Bebee, 2008) (DesRoches C. M., Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians, 2015). HITECH incentive payments are only achieved by meeting Meaningful Use criteria which include but are more extensive than the seven IT functionalities available in these surveys and panel for analysis (Hsiao, Hing, & Ashman, No. 75, 2014). These differences between Small and Medium/Large Practices in additions, retentions, and reductions in IT functionality indicate Small Practices adopt EHR

functionalities at lower rates than Medium/Large Practices, and these lower rates persist over time.

Changes over time in IT Adoption Scores for Primary Care physicians: Primary care practitioners' IT Adoption changed from lagging by about 25 percent in the baseline period to being about the same level of IT Adoption in the second period. Overall, for the Full Sample, "primary care physician" was associated with increased IT Adoption ( $p < 0.01$ ).

Older Physicians in Small Practices Adopted IT at Significantly Lower Rates: For early starters in practice, a significant drop in IT Adoption for small practices was evident. In the Small Practice Sample, for every one unit of increase in the IT Adoption Score, the rate of adoption the earliest category of physicians in this study (began practicing in 1965 or before), was on average lower by 0.39 ( $p < 0.01$ ).

Practice Characteristics that influence IT Adoption: Managed care was associated with increased IT adoption for both small and medium/large practices: in Small Practices as well as Medium/Large Practices, increased managed care was associated with increased IT Adoption ( $p < 0.001$ ).

While levels were not statistically significant, revenues from Medicare were associated with slightly lower IT adoption. This is important, since chronic care management reliance on telehealth and telemedicine capabilities assumes a foundational EHR to be in place in physician practices. Lower EHR adoption will make adoption of these additional chronic care management IT capabilities more challenging for small practices, foretelling greater on-going struggles among Small Practices to keep up with growing IT-enabled reimbursement trends unless the HITECH

programmatic and other policy interventions are successful in helping close the IT Adoption gap between Small and Medium/Large practices.

These findings support the correctness of implementing the HITECH Act as part of the ARRA, to bolster and incent efforts to establish EHRs in physician practices. Impact to policy would be significant if Meaningful Use does not achieve its desired outcomes of widespread adoption of EHRs in physician practices. Consistent with this idea, Meaningful Use Stage 2 has been recently extended and Stage 3 delayed by a year to 2016–2017, to give lagging practices more time to meet and report achievement of Stage 2 criteria (HITC Staff, 2015). Only 44% of physician practices have continued in the Meaningful Use program through Stage 2 as of 2015, so the ONC is allowing more time for providers to meet Stage 2 requirements and earn the incentive payment, after which time the incentive shifts to a penalty of reduced CMS reimbursement (HITC Staff, 2015) (Blumenthal & Tavenner, 2010). Although EHR adoption is increasing in physician practices and hospitals through the period of Meaningful Use implementation (2011–2018), support for practices with significant percentages of Medicare revenues could be continued beyond the “incentive period” when the financial process begins to penalize those eligible providers not meeting Meaningful Use criteria. This study provides evidence that small practices with Medicare patients are less likely than medium/large practices to adopt EHRs, suggesting policy continue to support smaller practices through incentives for a longer period of time than medium/large practices. The future of chronic care management and telehealth/telemedicine capabilities to support patient engagement (i.e., non-face-to-face care with these patients) is central to CMS accomplishing its strategy to make care for these patients more cost-effective through information technology. Policy may be crafted to differentiate between small and larger practices regarding timing criteria for accomplishment of Meaningful

Use functionality, to continue to encourage adoption among smaller practices through extended incentives, and to simply give small practices more time to adopt EHR functionality. This study provides evidence that such policy support would potentially improve EHR adoption rates overall, in particular among small practices, since smaller practices adopt EHR functionality at lower rates than their larger counterparts, with IT adoption more susceptible to the effects of individual physician characteristics. This policy support would be appropriate as part of the CMS strategy to create digital care processes for chronic and other care management, a phenomenon particularly prominent among practices caring for the growing Medicare demographic.

#### Data Issues

Missing data: certain variables had only minor numbers of missing data. To rid the sample of these, for each variable with missing values a sample variable was created for dropping missing values from the original sample, based on the extent and number of missing values.

Several independent variables had changes for the same physician between the baseline and second periods, such as a few for gender, year graduated (used as the basis of calculating “year began practicing”), and geography for which 319 of 4,428 changed locations between filling out the survey in 2000–2001 and 2004–2005. These changed data elements were excluded from the sample for instances in which they could make a difference, such as changes greater than ten in “practice size”. In other instances, such as for “gender” and “year began practice”, only a few values changed from baseline to the second period, so the baseline value was used – this small amount of variability in the sample data was not seen as a threat to the analysis.

No vendor data: This sample does not contain data about which vendor supplied the EHR software systems used in the physician practices or take into consideration how different types of

software and vendor competency influence adoption. This type of data would be useful because vendor software packages vary widely in terms of user-friendliness and vendor support, so vendor-identifying data elements would be helpful to understand the influence of vendor software product and level of vendor support on IT adoption, and the differences of these effects on Small or Medium/Large Practices' IT adoption and de-adoption rates.

Sampling bias: Bias could be introduced due to the possibility that those physicians who answered the survey had the time to do so, which could reflect a practice that was not as busy as others, and therefore might also have more time to devote to implementing EHR functionality. This would create a bias towards increased adoption in the sample, more than what is truly reflective of or generalizable to the universe of office-based practices.

#### Relationship to Rogers' Theory of Diffusion of Innovation:

Roger's Diffusion of Innovation Theory identifies five categories of participants in adoption of disruptive technologies, Innovators, Early Adopters, Early Majority, Late Majority and Laggards (Rogers, 1981). Rooted in sociological theory, Rogers' Innovators (2.5%), and Early Adopters (13.5%), are the early key groups to initiate adoption of a new technology, such as EHR systems for use in physician practices (Rogers, 1981). Broad adoption of such innovation does not typically occur until the Early Majority (34%) engages in the use of the new technology, eventually moving into the Late Majority (34%), with Laggards (16%) who only adopt the new technology when they must (Robinson, 2009). Later work observes an adoption chasm that lies between the Innovator/Early Adopter phases and the Early Majority phase (Robinson, 2009). Because groups following the change-seeking Innovators and Early Adopters are not naturally inclined to seek new ways of doing work, engaging the Early Majority is an especially

challenging phase to achieve. Thus a successful adoption of a new, disruptive technology, such as an EHR system, throughout an organization must traverse this chasm. Disruptive initiatives often fade or get stuck at this point, failing to make it to the Early Majority phase, a fate that ultimately squelches the initiative's momentum that would carry it to widespread adoption.

Adoption of such technologies that cannot span this chasm thus does not reach ubiquitous use.

Also according to Rogers' Theory of the Diffusion of Innovation, there exist five key Enablers of Adoption, including the bolded elements below which are likely to play an active role in influencing adoption of EHR functionalities among physicians in their practices in this study and sample:

**Relative Advantage:** Users can see a perceived value to the innovation. In the case of this study, greater numbers of physicians (users) in larger practices means greater probability of having individuals who think this way to perceive value in use of EHR functionality;

**Compatibility with Existing Values and Practices:** if the new technology is viewed as being consistent with the values of the user and practices already in place, it is more likely to be adopted. In the case of this study, this is consistent with the lower adoption among physicians in the oldest groups, who would potentially view EHR functionality as foreign to their views of normal ways to practice medicine.

**Simplicity and Ease of Use:** The easier the new technology is to use, the more likely it is to be adopted. In this study, support infrastructure that may be more readily available in medium/large practices would ease the use of the EHR functionalities.

**Trialability:** Innovation that carries little risk to the person trying it out is more likely to be adopted. In this study, EHR adoption would represent a higher risk to physicians in small



practices vs. larger ones, as a failure would be potentially more devastating and difficult to recover from. In larger practices, the new technology could be attempted on a trial basis, thus presenting less risk. Thus the new technology would be likely to be adopted at lower rates among physicians in small practices than medium/large practices.

**Observable Results:** Technology that produces visible results is more likely to be adopted. In this study, the ability to observe results would not vary between small or medium/large practices, but would likely be observable in any practice adopting the EHR functionalities (Robinson, 2009).

Applying Rogers' theory to adoption of EHRs by physicians for use in their practices, small practices with lower rates of adoption may be experiencing the difficulty of making it across the adoption chasm between Early Adopters and Early Majority. Their slower rates of adoption, vulnerability to individual physician characteristics, and overall lower IT Adoption Scores may be associated with the struggles of surpassing the initial Innovator and Early Adopter stages of adoption. Due to lack of expensive IT support infrastructure, personnel for additional tasks associated with the implementations, and the needed financial capacity to support IT, these small practices may be less able to make it from Innovator/Early Adoption to Early Majority and Late Majority phases of Roger's Diffusion Curve. The simple fact that there are five phases in Rogers' theory may outstrip the numbers of types of personalities comprising these groups in a small practice, making the effect of an individual physician's tendencies overpowering to the effects of other physician or practice variables, and more heavily influencing IT adoption in these small practices. The results of this study show small practices adding functionality at lower rates and experiencing slightly higher rates of de-adoption than larger practices over the panel's six-year time period. This evidence supports the notion that small practices struggle more to

adopt as well as maintain use of the new technology, resulting in small practices falling further behind medium/large practices in IT adoption as time goes on. On average, in the context of the overall environment, this study provides evidence that smaller practices experiences lower rates of EHR adoption driven by effects of gender, primary care, age, race, and practice size to leap the “adoption chasm.”

Generalized across the universe of office-based physician practices these findings are consequential, considering the priority, investment, and attention being paid to incent physician practices to adopt EHR systems through the HITECH Meaningful Use program and new CMS reimbursement codes for Chronic Care Management (CPT Code 99490) and other digitally supported care processes (Sullivan, 2015) (American Academy of Family Physicians, 2014) (Wicklund, 2013) (Wicklund, 2014). Currently small practices are struggling to achieve Meaningful Use through Stage 2 compared to larger practices (DesRoches C. M., 2015) (HITC Staff, 2015). This result portends diminished success of the goals of HITECH’s Meaningful Use program for small practices unless an intervention is made through policy adjustments and programs. For instance, HITECH could allow disproportionate support and more time to small practices over their medium/large practice counterparts to adopt EHRs and meet Meaningful Use criteria. Recent statistics for Stage 2 compliance indicate that 22% of physician practices that achieved Stage 1 Meaningful Use criteria are abandoning the Meaningful Use program at the original reporting qualification deadline for Stage 2, a factor that contributed to the ONC extending the Stage 2 reporting period by one year to the end of calendar year 2015 (Dvorak, 2015). Also, 55% of physicians do not plan on attesting for Meaningful Use Stage 2 (HITC Staff, 2015). Analysis of characteristics and factors associated with small vs. medium/large practices in the group abandoning Meaningful Use Stage 2 would provide further insight into the issues of

and solutions to small practices struggling to adopt EHR systems. This research should be done to fine-tune programs and policy to support adoption of EHR functionalities by small versus medium/large practices, as the drivers of adoption vary for each of these size practices.

The HITECH Meaningful Use program shifts Stage by Stage from incentive rewards (i.e., money reimbursed to physician practices that meet increasingly comprehensive Meaningful Use Stages 1, 2, and 3 criteria) to penalties (i.e., reduced CMS Medicare and Medicaid reimbursement for those physician practices not achieving Meaningful Use criteria) (Blumenthal & Tavenner, 2010) (Dvorak, 2015) (Drazen, 2011) (HITC Staff, 2015) (Blumenthal & Tavenner, 2010). This dissertation provides evidence that small practices were increasingly less able than their medium/large counterparts to achieve EHR adoption in the pre-ACA environment, and provides a baseline against which the HITECH incentive program in the post-ACA environment can be compared. Current evidence from studies of adoption rates in the ACA environment show that smaller practices and hospitals continue to lag in their capacity and ability to adopt EHR systems, even with financial incentives and looming penalties (Ashish K. Jha, 2010) (DesRoches C. M., 2015). This bodes negative implications for the long-term viability of smaller practices in two ways. First, smaller practices will experience reduced levels of Medicare and Medicaid reimbursement that will be associated with lower EHR adoption rates and assumed commensurate inability to meet Meaningful Use criteria. Second, small practices will experience a more pronounced effect of individual physician and practice characteristics associated with lower adoption rates such as gender, age, race, and primary care in this study. Combining this evidence with current and upcoming financial penalties for lack of achievement of Meaningful Use criteria (criteria which are mirrored in the seven IT functionalities measured in this survey and analyzed in this study), plus missing opportunities for increased reimbursement for CCM

and telehealth services, paints a challenging post-ACA picture for the future of small practices unless some intervening policy or program is put in place (Steed, 2014) (Wicklund, CMS urged to reimburse docs for mHealth diabetes tools, 2014).

Visually this threatening progression looks like this:

1) Difficulty in implementing and retaining EHR functionality among smaller practices and those practices with greater percentages of revenues from Medicare and managed care → 2) lower ability of these practices to achieve Meaningful Use criteria and receive HITECH financial incentives through 2016 → 3) greater probability of these practices being hit with increasing Meaningful Use-related penalties associated with not achieving Meaningful Use criteria as of 2015 onward + increasing percentages of revenues for all practices from Medicare and Medicaid due to implementation of ACA and growth of the Medicare demographic due to aging baby-boomers → 4) increased numbers of small and medium/large practices with greater percentages of managed care revenue sources associated with ACA → 5) reduced financial margins for smaller practices threatening their viability → 6) increased struggle of practices to implement EHRs and achieve Meaningful Use, thus being in a disadvantaged position regarding HITECH Meaningful Use penalties → 7) inability of practices without comprehensive EHR platforms to adopt additional digital capabilities that qualify them for payment using new reimbursement codes from CMS for Chronic Care Management (CCM) (CPT code 99490), telemedicine, and telehealth capabilities, leading these practices to fall further behind financially (Wicklund, 2014; Wicklund, 2013).

So, are two great government programs and policies that are intended to help providers adopt EHR systems in their practices and patients get access to providers through increased access to

health insurance, ARRA (HITECH and Meaningful Use incentives) and ACA, working together in ways that might actually threaten the viability of small practices? Are small practices and those practices that have a greater percentage of their revenue sources as Medicare and managed care more vulnerable to these negative effects since reimbursement rates for Medicare will be dependent upon EHR adoption (and retention)? This study would say “yes,” based on the EHR adoption experience of this panel pre-ACA and pre-ARRA combined with evidence from the experience thus far of physician adoption of EHR functionalities during the post-ARRA and post-ACA environment.

Smaller practices and practices with revenues comprised of greater percentages of Medicare and managed care may be potentially harmed financially due to the stimulus program. This program provides incentives to them to adopt EHRs, rewards that turn to penalties later if Meaningful Use criteria are not achieved. In addition to this, the ACA increases access to reimbursement through insurance programs as well as increased numbers of Medicare beneficiaries due to growth in the Medicare population—these characteristics are associated with lower rates of EHR adoption, which increases the probability these practices will fall in the penalty versus reward category.

Additional research should be done to better understand “de-adoption” of EHR functionalities, and the practice and physician characteristics and conditions that are associated with de-adoption. This research should examine the EHR functionalities that are involved in de-adoption, as well as how these functionalities differ for small vs. medium/large practices to see if there are patterns in de-adoption that could be addressed through policy or programmatic interventions. Studying de-adoption as well as adoption provides the opportunity to examine adoption in a more robust fashion, and may create actionable findings to improve efficiency and effectiveness of EHR adoption for practices of any size.

Efficiency of EHR adoption can thus be thought of and defined for this research as EHR functionality retentions, plus additions, minus reductions (or de-adoptions) over time.

### **Study Limitations and Strengths**

While it is important that physicians filled out these surveys directly, physician over-reporting is a limitation of the study, since physicians tend to over-report when taking surveys (Cleary & Jette, 1984). However, the seven IT-related questions comprised a small subset of the total survey, which covered a broad scope of questions about practices, geography, satisfaction, revenue sources, and other non-IT topics. So physician respondents may not have been more motivated to single out the IT-related questions if EHR adoption was the sole focus of the survey. If this survey had been focused solely on EHR adoption or IT use in practices, it may have attracted physicians who were attentive to IT and EHR adoption, potentially introducing bias into their responses. The survey contained seven IT-related questions. These seven questions represent a decent cross-section of EHR types of functionality. However, it would have been desirable to have more IT-related questions to analyze. Note: the 2004–2005 survey contains nine IT-related questions, seven of which are the same as the IT questions in the 2000–2001 survey.

This study applies to office-based physician practices—study results regarding EHR adoption may not be generalizable to EHR adoption in governmental or employed physician settings.

This study does not address which IT functionalities specifically were de-adopted, retained, or added among the small and medium/large physician practices, rather focuses on increases in the IT Adoption Score between baseline and second periods, a measure which is a combination of all changes. Research studying de-adoption relative to specific EHR functionalities would be

important to conduct to gain further insight into the inner workings of the adoption/de-adoption mechanisms.

Since adoption and de-adoption of EHR functionalities are not concentrated into groupings of similar functionalities or levels, effects of physician and practice characteristics on adoption of each type of functionality are not addressed in this analysis, only the total IT Adoption Score.

### **Strengths**

Notwithstanding the limitations mentioned above, the study has strengths that bear mentioning. These include: the study sample is built from data from randomly selected national samples and well-developed survey instrument, containing a good-sized panel of physicians who filled out the surveys, rather than responses provided by administrative representatives or other ancillary personnel from the physicians' practices. Also, in addition to the seven IT-related questions, a rich set of physician and practice characteristic variables are available in the datasets, which provides the opportunity to estimate the influence of a variety of physician and practice characteristics on the dependent variable, i.e., IT Adoption Score.

### **Policy Implications and Future Research Directions**

These results apply to the pre-ARRA/HITECH and pre-ACA environment. In addition to providing further understanding regarding early adoption behavior and influencers, the study sets a baseline against which post-ARRA/HITECH and ACA behaviors and influencers can be compared. A foundation is thus laid for examining ARRA/HITECH and post-ACA EHR results to inform policy and programs for HITECH and further legislation and regulations. Evidence that small practices lag medium/large practices in achieving comprehensive EHR adoption in the pre-ACA environment provides specifics for evaluating the HITECH incentive programs at the level

of physician and practice characteristics. Additional research on the IT adoption experience of small and medium/large practices and influences of physician and practice characteristics will further inform the policy, desired targets, and reimbursement mechanisms of HITECH and ACA. Interventions can be shaped in the case of detractors, and support programs for enhancers of EHR adoption, directed to address specific disadvantaged groups such as smaller practices.

Insights into functionality de-adoption and its relationship to physician and practice characteristics should be further studied to understand influencers of de-adoption. De-adoption should be understood at the level of specific IT functionalities and physician and practice characteristics. De-adoption trends should be closely monitored to inform appropriate policy and programmatic interventions. Further study in these areas is warranted, with policy and efforts directed towards preventing de-adoption and mitigating negative effects on EHR adoption through HITECH and CMS reimbursement policies.

CTS also conducted surveys in 2008 and 2012, called the Health Tracking Study – Physician Survey, providing an opportunity for comparative research with this study of 2000–2001 and 2004–2005 surveys. These later Physician Surveys were conducted with a revised methodology but asked many similar questions. A study should be considered to compare 2008 and 2012 results with results from this dissertation, giving careful thought to design due to changes in methodology and sample. Continued work using the CTS surveys to examine IT adoption by physicians for use in their practices should be conducted.

Further studies should also be done to examine the effect of independent variables reflecting physician and practice characteristics, on IT Adoption scores during ARRA/HITECH and ACA time periods from subsequent rounds of the ICPSR Center for Studying Health System



Change—Community Tracking Study (CTS)-Physician Survey. This is important not only because of the need to track progress of the HITECH Meaningful Use Policy and programs, but for additional digitally enabled reimbursement changes, building upon the Meaningful Use EHR foundation. Chronic Care Management (CPT Code 99490), Oncology Care Management, and other telehealth and telemedicine reimbursement codes being studied and introduced by CMS signal the types of financial incentives available to physicians that may reward EHR functionality adoption and create important new opportunities for ensuring financial viability of their practices into the future.

<b>Table 5-1: Descriptive Statistics of Physician Panel 2000–2001 – 2004–2005</b>					
<b>Panel Sample* (N = 3,164)</b>					
<b>Variables</b>	<b>2000–2001 Mean (SD/%)</b>	<b>2004–2005 Mean (SD/%)</b>	<b>Min/ Max</b>	<b>N</b>	<b>%</b>
IT Adoption Score	1.97 (1.80)	2.57 (1.98)	0 / 7	3,164	
Practice Size					
Small (ref.)(1-4 physicians)	1,739 (54.96%)	1,812 (57.27%)	1 / 4		54.96
Med/large (5+ physicians)	1,425 (45.04%)	1,352 (42.73%)	5 /		45.04
Practice ownership				3,164	100.00
0 Owner both periods (ref.)	2,064				65.23
1 Owner neither period		724			22.88
2 Owner 2000–2001 only	116 (3.67)				
3 Owner 2004–2005 only		260			8.22
Fiscal characteristics					
% Rev. Medicare	30.02	30.25	0/100	3,164	
% Rev. Medicaid	12.80	13.13	0/100	3,164	
% Rev. Mgd. Care	46.37	43.94	0/100	3,164	
<b>Physician Characteristics</b>	<b>N</b>				
Female (referent)	739			3,164	23.36
Year began practice					
1 1996+ (referent)	536 (16.94%)				16.94
2 1991-1995	567 (17.92%)				34.86
3 1986-1990	580 (18.33%)				53.19
4 1981-1985	567 (17.92%)				71.11
5 1976-1980	412 (13.02%)				84.13
6 1971-1975	256 (8.09%)				95.83
7 1966-1970	114 (3.60%)				95.83
8 1965 or earlier	132 (4.17%)				100.00
Primary care					
Primary Care (referent)	1,791			3,164	56.61
Career satisfaction				3,164	100.00
Satisfied	2,550 (80.59%)	2,553 (80.92%)			
Not satisfied	614 (19.41%)	602 (19.08%)			
Race				3,164	100.00
Non-white (referent)	616				19.47
White	2,548				80.53

**Table 5-2: Changes in Adoption of EHR IT functionalities among panel of physicians  
2000–2001 – 2004–2005 Full Panel Sample**

Adoption of EHR Functions (rank 1-7)	2000–2001 – 2004–2005 IT Functionality Usage (Adoption)						Totals
	N (%)	Base Rate (%)	Retained (%)	Dropped (%)	Added (%)	Neither Period (%)	Net total use (%)
<b>IT_TRT</b> Treatment guidelines (1)	3,164 (100)	1623 (51.30)	1,271 (40.17)	352 (21.69)	683 (21.59)	858 (27.12)	1,954 (61.76)
<b>ITCLIN</b> Exchange data w/ other MDs (6)	3,164 (100)	1,118 (35.34)	728 (23.01)	1,443 (45.01)	603 (19.06)	1,443 (45.61)	1,331 (42.07)
<b>ITNOTES</b> Patient notes or med lists (4)	3,164 (100)	989 (31.26)	723 (22.85)	266 (8.41)	551 (17.41)	1,624 (51.33)	1,274 (40.27)
<b>IT_Form</b> Formularies (2)	3,164 (100)	836 (26.42)	550 (17.38)	286 (9.04)	737 (23.29)	1,591 (50.28)	1,287 (40.68)
<b>ITRMNDR</b> Preventive Reminders (3)	3,164 (100)	763 (24.12)	444 (14.03)	319 (10.08)	484 (15.30)	1,917 (60.59)	928 (29.33)
<b>ITCOMM</b> E-mail w/ patients (7)	3,164 (100)	574 (18.14)	342 (10.81)	232 (7.33)	372 (11.76)	2,218 (70.10)	714 (22.57)
<b>ITPRESC</b> Write prescriptions with EHR (5)	3,164 (100)	327 (10.34)	199 (6.29)	128 (4.05)	441 (13.94)	2,396 (75.73)	640 (20.23)

**Table 5-3: Trends in averages of physician use of electronic health records (EHRs) by full sample, small practices, and medium/large practices among panel over time (2000–2001 – 2004–2005).**

	Panel Dataset (N = 1,739) IT Adoption Small Practices (1-4 physicians)			Panel Dataset (N = 1,425) IT Adoption Medium/Large Practices (5+ physicians)			Full Panel Dataset (N = 3,164) IT Adoption All Practices		
IT Adoption Score	Coeff.	SE	95% CI	Coeff.	SE	95% CI	Coeff.	SE	95% CI
Female	-0.05	0.10	[-0.25,0.14]	0.06	0.12	[-0.17,0.30]	-0.17x10 <sup>-2</sup>	0.08	[0.15,0.15]
Year began practice									
1: 1996+ ref.									
2: 1991-1995	0.30	0.15	[0.02,0.59]	0.07	0.15	[-0.22,0.37]	0.16	0.10	[-0.04,0.37]
3: 1986-1990	0.18	0.15	[-0.11,0.46]	-0.11	0.16	[-0.41,0.20]	0.17	0.11	[-0.19,0.22]
4: 1982-1985	0.34	0.14	[0.06,0.62]	0.15	0.16	[-0.17,0.46]	0.22*	0.11	[0.01,0.43]
5: 1976-1980	0.13	0.15	[-0.16,0.43]	0.21	0.18	[-0.15,0.57]	0.13	0.12	[-0.10,0.36]
6: 1971-1975	0.10	0.17	[-0.23,0.44]	0.10	0.22	[-0.34,0.54]	0.06	0.13	[-0.20,0.33]
7: 1966-1970	0.05	0.21	[-0.37,0.47]	-0.34	0.33	[-0.10,0.32]	-0.12	0.18	[-0.47,0.24]
8: 1965/prior	-0.11	0.20	[-0.50,0.28]	0.35	0.40	[-0.43,1.13]	-0.10	0.17	[-0.44,0.24]
Primary vs. Specialty									
Primary Care	0.14	0.08	[-0.02,0.30]	0.18	0.10	[-0.02,0.38]	0.17**	0.06	[0.04,0.30]
Career Satisfaction									
Satisfied	-0.02	0.09	[-0.21,0.16]	0.17	0.13	[-0.08,0.43]	0.05	0.0	[-0.10,0.20]
Race									
Non-white	-0.19	0.10	[-0.38,-0.00]	-0.15	0.13	[-0.41,0.11]	-0.19**	0.08	[-0.35,-0.40]
Practice ownership									
Owner_neither	0.31	0.13	[0.05,0.57]	-0.09	0.11	[-0.31,0.13]	0.08	0.08	[-0.08,0.24]
Owner_base	0.33	0.22	[-0.10,0.76]	-0.22	0.25	[-0.71,0.26]	0.09	0.16	[-0.43x10 <sup>-2</sup> ]
Owner_y5only	0.27	0.18	[-0.10,0.63]	0.03	0.16	[-0.29,0.35]	0.15	0.12	[-0.45x10 <sup>-2</sup> ]
Fiscal characteristics									
% Rev MCARE	0.52x10 <sup>-3</sup>	0.18x10 <sup>-2</sup>	[-0.30x10 <sup>2</sup> ,0.40x10 <sup>-2</sup> ]	-0.43x10 <sup>-2</sup>	0.24x10 <sup>-2</sup>	[-0.90x10 <sup>-2</sup> ,0.34x10 <sup>-3</sup> ]	-0.14x10 <sup>-2</sup>	0.14x10 <sup>-2</sup>	[-0.32x10 <sup>-2</sup> ,0.14x10 <sup>-2</sup> ]
% Rev MCAID	-0.82x10 <sup>-3</sup>	0.26x10 <sup>-2</sup>	[-0.59x10 <sup>-2</sup> ,0.43x10 <sup>-2</sup> ]	0.47x10 <sup>-3</sup>	0.33x10 <sup>-2</sup>	[-0.62x10 <sup>-2</sup> ,0.71x10 <sup>-2</sup> ]	-0.42x10 <sup>-3</sup>	0.21x10 <sup>-2</sup>	[-0.51,-0.24]
%Rev MC	-0.47x10 <sup>-3</sup>	0.15x10 <sup>-2</sup>	[-0.35x10 <sup>-2</sup> ,0.25x10 <sup>-2</sup> ]	-0.16x10 <sup>-2</sup>	0.18x10 <sup>-2</sup>	[-0.52x10 <sup>-2</sup> ,0.21x10 <sup>-2</sup> ]	-0.90x10 <sup>-3</sup>	0.12x10 <sup>-2</sup>	[0.45,0.97]
constant	Small 0.18 (0.16)			Large .90 (0.20)			(Full) .71 (0.13)		
*p<0.05 **p<0.01 ***p<0.001									

<b>Table 5-4: Changes in IT Adoption Scores among all practices: addition, retention, or reduction of EHR functionality among full panel physicians 2000–2001 – 2004–2005</b>									
<b>IT Adoption Scores: Baseline v. 2004–2005</b>	0	1	2	3	4	5	6	7	<b>Total Beginning Distribution (%)</b>
0	364	175	142	84	24	17	11	5	822 (25.98)
1	137	166	154	126	62	36	19	8	708 (22.38)
2	49	103	134	123	93	42	20	8	572 (18.08)
3	17	43	77	101	97	53	26	8	422 (13.34)
4	8	22	38	60	80	48	35	18	309 (9.77)
5	2	6	11	23	31	44	28	23	168 (5.31)
6	3	2	2	13	9	23	28	25	105 (3.32)
7	1	1	2	3	3	6	11	31	58 (1.83)
<b>Total Ending Distribution (%)</b>	581 (18.36)	518 (16.37)	560 (17.70)	533 (16.85)	399 (12.61)	269 (8.50)	178 (5.63)	126 (3.98)	<b>3,164 (100.0)</b>

<b>Table 5-4a: Changes in IT Adoption Scores among small practices: addition, retention, or reduction of EHR functionality among panel physicians 2000–2001 – 2004–2005</b>									
<b>IT Adoption Scores Base v. 2004–2005</b>	0	1	2	3	4	5	6	7	<b>Total Beginning Distribution (%)</b>
0	273	115	79	44	14	5	4	1	535 (30.76)
1	97	112	95	67	27	16	4	5	423 (24.32)
2	35	67	71	70	43	16	4	1	307 (17.65)
3	9	26	43	61	43	27	7	3	219 12.59
4	5	11	24	30	36	21	10	6	143 (8.22)
5	2	4	4	6	15	17	7	4	59 (3.39)
6	3	1	2	7	4	5	8	3	33 (1.90)
7	1	0	2	3	0	3	6	5	20 (1.15)
<b>Total Ending Distribution (%)</b>	425 (24.44)	336 (19.32)	320 (18.40)	288 (16.56)	182 (10.47)	110 (6.33)	50 (2.88)	28 (1.61)	<b>1,739 (100.0)</b>

<b>Table 5-4b: Changes in IT Adoption Scores among medium/large practices: addition, retention, or reduction of EHR functionality among panel physicians 2000–2001 – 2004–2005</b>									
<b>IT Adoption Scores Baseline v. 2004–2005</b>	0	1	2	3	4	5	6	7	<b>Total Beginning Distribution (%)</b>
0	91	60	63	40	10	12	7	4	247 (20.14)
1	40	54	59	59	35	20	15	3	285 (20.00)
2	14	36	63	53	50	26	16	7	265 (18.60)
3	8	17	34	40	54	26	19	5	203 (14.25)
4	3	11	14	30	44	27	25	12	166 (11.65)
5	0	2	7	17	16	27	21	19	109 (7.65)
6	0	1	0	6	5	18	20	22	72 (5.05)
7	0	1	0	0	3	3	5	26	38 (2.67)
<b>Total Ending Distribution (%)</b>	156 (10.95)	182 (12.77)	240 (16.84)	245 (17.19)	217 (15.23)	159 (11.16)	128 (8.98)	98 (6.8)	1,425 (100.00)

<b>Table 5-4c: Changes in IT Adoption Scores among full, small, and medium/large sample practices: addition, retention, or reduction of EHR functionality among panel physicians 2000–2001 – 2004–2005</b>			
<b>IT Adoption</b>	<b>Full (%)</b>	<b>Small (%)</b>	<b>Medium/Large (%)</b>
<b>Additions</b>	1,510 (47.7)	777 (44.7)	818 (57.4)
<b>Retentions</b>	948 (30.0)	583 (33.5)	365 (25.6)
<b>Reductions</b>	706 (22.3)	379 (21.8)	242 (17.0)
<b>Total</b>	3,164 (100.0)	1,739 (100.0)	1,425 (100.0)

<b>Table 5-5: Linear regression model of change in total IT Adoption Score for full panel and stratified by practice size (Small and Medium/Large Practices)</b>			
<b>Characteristics</b>	<b>Panel: Full</b>	<b>Panel: Small Practice Size</b>	<b>Panel: Med/Large Practice Size</b>
	<b>Est. (+/- SE)</b>	<b>Est. (+/- SE)</b>	<b>Est. (+/- SE)</b>
Practice size small	-0.58*** (0.06)		
Year total IT	-0.39*** (0.02)	-0.40*** (0.00)	-0.39***(0.02)
Female (ref.)	-0.17* (0.07)	-0.18 (0.07)	-0.16 (0.11)
Year began practice			
1 1996+ (ref.)			
2 1991-1995	0.14 (0.10)	0.24 (0.13)	0.07 (0.14)
3 1986-1990	-0.02 (0.10)	0.09 (0.13)	-0.11 (0.14)
4 1982-1985	0.17 (0.10)	0.23 (0.13)	0.13 (0.15)
5 1976-1981	0.11 (0.11)	0.05 (0.14)	0.24 (0.17)
6 1971-1975	-0.03 (0.12)	-0.01 (0.15)	-0.01 (0.21)
7 1966-1970	-0.26 (0.16)	-0.13 (0.19)	-0.44 (0.31)
8 1965/earlier	-0.35* (0.16)	-0.39* (0.19)	-0.02 (0.36)
Primary care	0.07 (0.06)	0.10 (0.07)	0.02 (0.10)
Career Satisfaction			
Satisfied (ref.)	0.03 (0.07)	-0.01 (0.09)	0.10 (0.12)
Race			
Non-white (ref.)	-0.17* (0.07)	-0.18* (0.09)	-0.11 (0.12)
Practice Ownership			
Owner both (ref.)			
Owner neither	0.18* (0.08)	0.33* (0.12)	0.08 (0.10)
Owner base	0.29 (0.15)	0.36 (0.20)	0.13 (0.23)
Owner 2004–2005	0.13 (0.11)	0.29 (0.17)	-0.00 (0.15)
Fiscal characteristics			
% Rev MCARE	-0.98x10 <sup>-3</sup> 0.13x10 <sup>-2</sup>	0.85x10 <sup>-3</sup> 0.16x10 <sup>-2</sup>	-0.36x10 <sup>-2</sup> 0.22x10 <sup>-2</sup>
% Rev MCAID	0.10x10 <sup>-2</sup> 0.19x10 <sup>-2</sup>	0.24x10 <sup>-2</sup> 0.24x10 <sup>-2</sup>	0.15x10 <sup>-3</sup> 0.31x10 <sup>-2</sup>
% Rev MC	0.19x10 <sup>-2</sup> 0.11x10 <sup>-2</sup>	-0.30x10 <sup>-3</sup> 0.14x10 <sup>-2</sup>	0.40x10 <sup>-2*</sup> 0.17x10 <sup>-2</sup>
constant	1.55 (0.13)	.94 (0.15)	1.62 (0.19)

\*p<0.05% \*\*p<0.01% \*\*\*p<0.001



**Table 5-6: IT Adoption among panel physicians and interaction with physician and practice characteristics for Baseline (2000–2001), Second Period (2004–2005), and Full Panel (2000-2005)**

Characteristics	ITAdoption: Baseline Period (2000-2001) Xβ Est. (SE)	ITAdoption Second Period (2004–2005) Xβ Est. (SE)	Δ ITAdoption Full Panel (2000-2005) Xβ Est. (SE)
Year	2000-2001	2004-2005	Panel (both)
Practice size			
Small	-0.52*** (0.07)	-0.94*** (0.07)	-0.38*** (0.07)
Gender			
Female	-0.43*** (0.08)	-0.41*** (0.09)	-0.00 (0.08)
Year began practice			
1: 1996+referent			
2: 1991-1995	-0.06 (-0.11)	0.13*** (0.12)	0.16 (0.10)
3: 1986-1990	-0.10 (0.11)	-0.04 (0.12)	0.02 (0.11)
4: 1982-1985	-0.12 (0.11)	0.14 (0.12)	0.22 (0.11)
5: 1976-1981	-0.06 (0.12)	0.09 (0.13)	0.13 (0.12)
6: 1971-1975	0.23 (0.14)	-0.15 (0.15)	0.06 (0.13)
7: 1966-1970	-0.36 (0.18)	-0.43* (0.20)	-0.12 (0.18)
8: 1965/earlier	-0.62*** (0.18)	-0.71*** (0.19)	-0.10 (0.17)
Primary vs. specialty			
Primary care	-0.25*** (0.07)	-0.05 (0.07)	0.17** (0.06)
Career satisfaction			
Satisfied	-0.06 (0.08)	-0.12 (0.09)	0.05 (0.08)
Race			
Non-white	0.07 (0.08)	-0.07 (0.09)	-0.19 (0.08)
Practice ownership			
owner neither	0.26** (0.09)	0.34*** (0.09)	0.08 (0.08)
owner base	0.50** (0.17)	0.50** (0.18)	0.09 (0.16)
owner y5 only	-0.06 (0.12)	0.32* (0.13)	0.15 (0.12)
Fiscal characteristics			
% Rev MCARE	0.13x10 <sup>-2</sup> 0.15x10 <sup>-2</sup>	-0.20x10 <sup>-2</sup> 0.16x10 <sup>-2</sup>	-0.15x10 <sup>-2</sup> 0.14x10 <sup>-2</sup>
% Rev MCAID	0.36x10 <sup>-2</sup> 0.21x10 <sup>-2</sup>	0.65x10 <sup>-3</sup> 0.22x10 <sup>-2</sup>	-0.42x10 <sup>-3</sup> 0.21x10 <sup>-2</sup>
% Rev MC	0.70x10 <sup>-2</sup> *** 0.12x10 <sup>-2</sup>	0.45x10 <sup>-2</sup> *** 0.13x10 <sup>-2</sup>	-0.90x10 <sup>-3</sup> 0.12x10 <sup>-2</sup>
constant	2.12 (0.14)	3.00 (0.15)	0.71 (0.13)

\* p<0.05, \*\* p<0.01, \*\*\* p<0.001

## Adoption of Electronic Health Records

### by Physicians for Use in Their Practices

#### Chapter 6

#### Conclusion

This dissertation is written in response to the struggles of physicians to adopt electronic health records (EHRs) for use in their practices, resulting in slow EHR adoption rates occurring through a time of great attention, financial support, and effort being paid to encourage such adoption (Buntin, Burke, Hoaglin, & Blumenthal, 2011).

In this study, the experience of small vs. medium/large practices is examined in particular, with distinctions and predictors of EHR adoption evaluated. At a time when high levels of investment, expectation, and effort in EHR adoption are under way nationally, persistent adoption challenges for physicians impede progress toward ubiquitous availability of these enabling technologies (Miller, West, Brown, Sim, & Ganchoff, The Value Of Electronic Health Records In Solo Or Small Group Practices, 2005). Improvements in quality of care and cost performance depend on physicians' use of EHRs rather than paper for most tasks (Kern, Barron, Kaushal, &

Dhopeswarkar, 2012) (Davis, Doty, Shea, & Stremikis, 2009). The study aim is to produce findings and recommendations to inform research and policy regarding EHR adoption in the hope of increasing EHR adoption by physicians for use in their practices, improving care quality, and reducing costs of care.

The three results chapters of this dissertation describe EHR adoption among physician respondents, including rates, characteristics, differences, and associations of various physician and practice characteristics to EHR adoption. The theoretical anchor of the dissertation is Rogers' Theory of Diffusion of Innovation, and connections between the study's findings are drawn to elements of this theory (Rogers, 1962, 1981).

Small vs. medium/large practice size is used to differentiate physician and practice characteristics that are associated with EHR adoption. The study identifies trends and changes in predictors of adoption, and evaluates rates of adoption and predictors over time. A conceptual framework is presented relating variables included in the analysis to EHR implementation, thus adding to the EHR adoption literature.

Three topics are examined in this study regarding physician adoption of EHRs. The first analysis develops a measure of EHR adoption using seven EHR functionality variables; the second analysis describes adoption rates and physician and practice characteristics by physicians in small and medium/large practices using a pooled dataset consisting of publicly available data from the Center for Studying Health System Change (HCS) and Community Tracking Study (CTS) – Physician Survey Round 3 (2000–2001) and Round 4 (2004–2005); the third analysis evaluates rates and drivers of adoption of EHR functionalities among a panel of physicians created from the restricted datasets from the same CTS survey rounds (ICPSR, 2015).

The time period (2000–2006) for these analyses reflects pre-ARRA/HITECH and pre-ACA experiences of Innovators and Early Adopters according to Rogers' Theory and as such, provides a baseline for evaluation and research of EHR adoption in the post-ARRA/HITECH and post-ACA era.

The dissertation consists of the following Chapters:

- Chapter 1 – Introduction
- Chapter 2 – Background and Literature Review
- Chapter 3 – Measuring Electronic Health Record Adoption: Development of the Dependent Variable
- Chapter 4 – Changes in Electronic Health Record Adoption by Physicians for Use in Small and Medium/Large Practices
- Chapter 5 – Panel Analysis of Physician Adoption of Electronic Health Record Capabilities
- Chapter 6 – Conclusion

Chapter 2 contains the Literature Review for this work, organized into four sections:

1. Electronic Health Records/Health Information Technology
2. Adoption of EHRs by physicians/physician practices/ambulatory settings
3. Diffusion of Innovations
4. Barriers and predictors of adoption

The three results chapters include: Chapter 3,, which presents results of the statistical analysis and development of the dependent variable; Chapter 4, which describes changes in adoption of EHRs by physicians for use in their practice, examining differences in physician and practice characteristics associated with adoption; and Chapter 5, which presents a panel analysis of physician adoption of EHR capabilities.

### Key Findings

Key findings for each results chapter are as follows:

Chapter 3—Measuring Electronic Health Record Adoption: Development of the Dependent Variable: This first results chapter in the dissertation is development of dependent variable “IT Adoption.” This chapter presents analysis of the seven “computer-use” information technology (IT) survey questions representing EHR-related functionalities and creates the dependent variable for measurement of IT adoption—Total IT Adoption Score. Total IT Adoption Score is then used as the dependent variable for the analyses in Chapter 4 and Chapter 5 of this dissertation. The seven variables included in the analysis are “use of the computer” for:

1. Treatment guidelines
2. Formularies
3. Preventive service reminders
4. Patient notes or medication lists
5. Writing prescriptions
6. Exchanging clinical data or images with other physicians

## 7. E-mail communication with patients about clinical issues

The same EHR-related questions were used in both Rounds 3 and 4 of the CTS – Physician Survey, allowing for analysis using the pooled and panel datasets described in Chapter 4 and Chapter 5, respectively.

In Chapter 3, techniques used to evaluate these seven IT variables include exploratory factor, Cronbach’s alpha, tetrachoric, and Guttman analyses to test the data for scaling among the data elements. Results indicated no scale, order, or subgrouping of functionality was found through application of these statistical techniques. The dependent measure for this dissertation was therefore defined as “IT Adoption Score,” a continuous variable and integer summing the number of “yes” answers to questions by physician respondents about their use of the seven IT functionalities in their practices.

Chapter 4—Changes in Electronic Health Record Adoption by Physicians for Use in Small and Medium/Large Practices: This chapter describes EHR functionality adoption by physicians in their practices and in particular, examines differences in adoption rates and associated characteristics among physicians in small (1–4 physicians) vs. medium/large (5+ physicians) practices. Descriptive statistics, Ordinary-Least-Squares (OLS) regression, Difference-in-Differences (DID) with cluster analysis, and Bootstrap confidence interval statistical techniques are applied to the pooled dataset created from publicly-available data from the CTS – Physician Surveys Round 3 (2000–2001) and Round 4 (2004–2005).

Key findings from this analysis include: both small and medium/large practices increased their use of EHRs; small practices were disadvantaged in their abilities to adopt EHRs; and the gap

between small and medium/large practices increased over the study period 2000–2001 to 2005–2005.

#### Chapter 5—Panel Analysis of Physician Adoption of Electronic Health Record System

**Capabilities:** This chapter presents the analysis of a physician panel sample of 3,164 physician respondents created from the CTS – Physician Survey, Rounds 3 and 4. The panel contained a majority of small practices (1,739 (54.96%) baseline 2000–2001 and 1,812 (57.27%) second period 2004-2005). The panel analysis shows small practices start at lower levels of EHR adoption than their medium/large counterparts, and medium/large practices increase EHR adoption at a faster rate than small practices. What’s new here is *de-adoption*. By analyzing the panel, visibility typically masked when quantifying only adoption rates is revealed into physician practices that are actually dropping EHR capabilities, a finding not noted before. Chapter 5 analysis looks further into whether physician and practice characteristics have the same weight in predicting adoption for small and medium/large practices.

Chapter 5 tests three hypotheses:

Hypothesis 1: Both small and medium/large practice samples will increase EHR adoption over time;

Hypothesis 2: Small practices (1–4 physicians) will adopt fewer EHR capabilities than medium/large practices (5+ physicians); and

Associated Hypothesis: predictors or drivers of EHR adoption among small practices will vary from those among medium/large physician practices. This hypothesis predicts drivers of adoption of EHR functionalities will differ in small practices vs. medium/large practices.

Results of the Chapter 5 panel analysis are consistent with the Chapter 4 pooled sample analysis. Small practice EHR adoption rates start at lower levels than those for medium/large practices in the 2000–2001 baseline period. Medium/large practices increase EHR functionality adoption at greater rates than small practices between baseline (2000–2001) and second (2004–2005) periods. Results indicate physicians in small practices adopt IT at lower rates than those in medium/large practices, on average, over time, supporting the study’s first hypothesis.

Small practices had lower adoption rates overall and lower increases in adoption over time, thus small practices fell further behind medium/large practices in IT Adoption over time, supporting the study’s second hypothesis. Not anticipated was the result that while overall IT Adoption Scores increase over time for panel, significant IT *de-adoption* occurs among all samples: full panel, small practices, and medium/large practices.

The findings of this chapter provide evidence that: 1) small practices adopt at lower rates over time than medium/large practices; 2) lower adoption is associated with physician characteristics of female, non-white, oldest groups, or in a small practice; and 3) small practices have, on average, lower adoption rates overall and lower increases in adoption over time, thus falling further behind medium/large practices in IT Adoption over time.

What’s new with panel analysis is evidence through analysis of the panel that small and medium/large practices are not only adopting but dropping or *de-adopting* functionalities as well. While overall IT Adoption Scores increase over time for the panel, significant IT functionality de-adoption occurs among all samples: the full panel, the small practices, and medium/large practices. De-adoption is a significant issue in these implementations, was common among all physician samples, and is muffled by the *net* increase in use of EHR functionalities. This finding



points out the flaw in simply measuring rates of EHR adoption—what is missed by doing this is the EHR de-adoption occurring at the same time, at about half the rate of EHR adoption. The panel analysis also allows for examination of predictors of IT adoption among small and medium/large practices and provides evidence that small practices lag behind medium/large practices, and that characteristics of female, non-white, oldest physician groups, and being in a small practice are associated with lower adoption rates; reimbursement from managed care is associated with greater rates of EHR adoption.

In summary, physicians in small practices adopt EHR functionality at lower rates than those in medium/large practices. Early policy, reimbursement, and programmatic efforts were ineffective in closing the gap between small and medium/large practices during the study time period. Additionally, this gap increased over time. Thus small practices fell further behind medium/large practices in IT Adoption over time. De-adoption of IT functionalities is muted by the overall net increase in IT adoption scores on average over time across small, medium/large practices, and full panel samples.

### Main Finding

The main finding of this dissertation is *de-adoption*. Study results reveal the de-adoption phenomenon, which is unreported in the literature to date; results also provide evidence of de-adoption of EHR functionality occurring at a rate of about half that of EHR adoption. This is a significant finding and should be studied further. Just as physician and practice characteristics that predict adoption are evaluated, the same characteristics should be analyzed for their association with de-adoption. Identification and exploration of de-adoption is needed to inform policy and programs intended to support and stimulate EHR adoption among physician practices.

Those policy and programs should be shaped to take de-adoption into account so that the masking effect of overall increases in EHR adoption do not mislead those involved to assume adoption is all that is happening or that once an EHR functionality is adopted that it is sustained. This chapter's findings also identify differences in de-adoption between small and medium/large practices, findings that can inform how policy and programs should vary for small versus medium/large practices. Based on the results reported in this dissertation, drivers of adoption vary between small and medium/large practices, and policy and programs should take these differences into account.

#### Relationship to Rogers' Diffusion of Innovation Theory

Rogers' Diffusion of Innovation Theory includes an Adoption Curve that identifies five groups that display gradually more adaptive tendencies in implementing disruptive technologies such as EHR functionalities including: Innovators (2.5%), Early Adopters (13.5%), Early Majority (34%), Late Majority (34%), and Laggards (16%) (Boston University School of Public Health, 2013). This dissertation addresses adoption rates and characteristics of those who would fall into Innovator and Early Adopter, and some movement into Early Majority categories. Tying study results of adoption rates to Rogers' Theory and can be used to calibrate policy and programs to the unique or varying characteristics of each of these categories of adopters (Robinson, 2009).

Four of five of the Enablers of Adoption according to Rogers' Theory of Diffusion of Innovation apply to this study and may explain differences between physician adopters based on their or their practices' characteristics:

- *Relative Advantage*: With perceived value to the innovation, greater numbers in larger practices means greater probability of having individuals who think in an innovative way to perceive value of EHR adoption;
- *Compatibility with Existing Values and Practices*: EHR capabilities are consistent with modern methods of medical practice, and this element is consistent with the dissertation study results of oldest groups with lower adoption rates, since their medical practice training and methods were learned before EHR systems were developed;
- *Simplicity and Ease of Use*: This element may contribute to lower adoption rates among small practices since they have less support infrastructure, making EHR adoption more difficult.
- *Trialability*: Innovation that carries little risk to the person trying it out would apply to EHR adoption being higher-risk to physicians in small practices vs. larger ones.
- *Observable Results*: EHR adoption in both small and medium/large practices would be observable so this element of Rogers' theory would apply to both groups (Robinson, 2009).

### Limitations and Strengths

Limitations of this study include use of self-reported data from physician respondents, who are reported to be prone to over-reporting (Cleary & Jette, 1984). Thus, results of EHR adoption rates might be biased upwards towards greater adoption than they are in actuality. A sampling bias is also introduced since those physicians who had time, responded to the survey. This might have biased the survey toward respondents who weren't as busy as other physicians and thus

who had time to fill out the survey, which might also translate to time available to go through the effort of adopting EHR functionality.

Another limitation of this dataset is that subsequent physician surveys from Center for Studying Health System Change used a different methodology, thus affecting the ability to use later survey rounds to continue to study EHR adoption trends and make comparisons between earlier and later rounds (Center for Studying Health System Change, 2011).

Strengths of the study include the availability of seven data elements representing relevant EHR functionalities. Also, CTS – Physician Survey Round 3 and Round 4 provide data from two time-points using the same survey instrument, with over three thousand of the same physicians responding to both rounds, making a panel dataset available for analyzing trends and characteristics associated with EHR adoption over time. The survey also provides nationally representative samples with large sample sizes.

#### Future Directions

This study of pre-ARRA/HITECH datasets provides a baseline upon which future research can be based, to evaluate post-ARRA/HITECH EHR functionality adoption by physicians for use in their practices. Relevant research would compare IT adoption experience of small and medium/large practices as well as examining influences of physician and practice characteristics, especially for small practices. Such future research is needed to further inform the policy, programs, desired targets, and reimbursement mechanisms of the post-HITECH and post-ACA era.

Especially important will be further research to assess post-ARRA/HITECH de-adoption along with adoption trends, drivers, and characteristics. Future research should closely monitor de-

adoption to inform policy and programmatic interventions. For instance, Meaningful Use compliance should measure both adoption and de-adoption for criteria from all three Meaningful Use Stages, to assure de-adoption of earlier reported functionality does not erode compliance with and goals of the HITECH policy and Meaningful Use program.

Additional research should repeat this dissertation's analysis using panel data from later surveys from CTS – Physician Survey Health Tracking Survey of 2008 and 2012. The Health Tracking Survey includes the same plus additional IT-related questions to those collected in the 2000–2001 CTS – Physician Survey. Since the survey methodology differs between the two surveys, subsequent panel analysis would not be directly comparable, but with care could be designed to look at same types of questions, analyzing similar questions and data elements; such analysis would provide valuable insight into continuing trends, drivers, and rates of EHR adoption in physician office settings. These subsequent time period analyses could then also be related to increasingly mature stages of Rogers' Diffusion of Innovation model, including Early Majority, Late Majority, and Laggards. Tying this research to Rogers' Theory of Diffusion of Innovation would inform policy and programs for supporting and sustaining adoption of EHR systems—adoption which is known to best deliver the hoped-for benefits of improved quality, service, and efficiency when physicians provide most care using an EHR system (Kern, Barron, Kaushal, & Dhopeswarkar, 2012).

Each results chapter of this dissertation provides opportunities for future research, including:

Chapter 3: Given the serious issues with measures of EHR adoption currently used in EHR adoption literature, an essential next step will be to develop a real measurement tool of EHR adoption that will account for the problems identified in this chapter (Institutes of Medicine

Committee on Patient Safety and Health Information Technology, 2012). This research should use an experience sampling methodology to test and improve the precision and effectiveness of the measurement tool. This would be a meaningful contribution to the literature and EHR adoption research, improving the reliability, comparability, and generalizability of studies requiring EHR adoption. This will assist in correcting for the current problem of wild differences in in EHR-related research and literature results (Institutes of Medicine Committee on Patient Safety and Health Information Technology, 2012).

Chapter 4: Further research should be done studying the differences between small practices v. medium/large practices in EHR adoption. The results from this analysis should be repeated using data from subsequent years' Health Tracking Survey – Physician Surveys that collect the same seven EHR-related data elements as well as a few additional ones. Using this study as baseline for post-ARRA/HITECH research, results of those policies can be assessed by comparing early, pre-ARRA/HITECH, pre-ACA EHR adoption rates and predictors as presented in this dissertation, to post-ARRA/HITECH, post-ACA time periods. This research should examine the IT adoption experience of small and medium/large practices, and the influences of physician and practice characteristics, especially for small practices. This future research will further inform the policy, desired targets, and reimbursement mechanisms of HITECH and ACA. It will also inform policy and programs for newly evolving EHR-dependent initiatives in the areas of Chronic Care Management (CCM), telehealth, chronic care management, and newly implemented CPT codes (such as CPT 99490) and reimbursement incentives for physicians. Just as described in Chapter 4 with the reimbursement incentives provided through up-coding that rewarded physician practices for their early EHR adoption efforts, these new chronic care management initiatives will be

important new reimbursement programs building upon that early work of EHR adoption with the goal of improving chronic care management and thus health care quality and cost performance.

These future research results should also be mapped to Rogers' Diffusion of Innovation Theory Adoption Curve in absolute terms, as well as according to changes in physician and practice characteristics associated with the adoption, so that policy and programs can be tuned to the evolving needs and preferences of adopters along each stage of the Adoption Curve.

Chapter 5: Further research stemming from the Chapter 5 panel analysis of EHR adoption should explore de-adoption that was identified in this chapter, to inform policy and programs intended to support EHR adoption. Future research should also assess post-ARRA/HITECH de-adoption along with adoption trends and characteristics and closely monitor de-adoption to inform policy and programmatic interventions and changes needed to address the reasons for EHR de-adoption. As in Chapter 4 pooled sample analysis, any relationship to Rogers' Diffusion of Innovation Theory Adoption Curve should be evaluated in absolute terms and for the association between physician and practice characteristics and EHR adoption over time. Post-ARRA/HITECH and post-ACA trends and changes can be tracked, using this dissertation's pre-ARRA/HITECH, pre-ACA results as the baseline for comparison. Using this study as baseline for post-ARRA/HITECH research, future research should examine IT adoption experience of small and medium/large practices, influences of physician and practice characteristics, especially for small practices, among a physician panel dataset. This will further inform the policy, desired targets, issues, and reimbursement mechanisms of HITECH and ACA (Bloomrosen, Starren, Lorenzi, Ash, Patel, & Shortliffe, 2011).

Future research should repeat this analysis using panel data from later surveys from CTS – Physician Survey, as those surveys have the same seven EHR-related variables as used in this study, plus additional IT-related questions. Because the subsequent Health Track Study – Physician Survey methodology changed from the CTS – Physician Survey methodology used for this dissertation subsequent panel analysis would not be directly comparable, but could be carefully designed to look at same types of questions and, with proper caveats, continue to understand trends and drivers of EHR adoption and de-adoption (Center for Studying Health System Change, 2011). Analysis of de-adoption for each of the seven EHR functionalities should be performed, to understand physician and practice characteristics associated with de-adoption. These subsequent analyses should be related to further stages of Rogers’ Diffusion of Innovation Adoption Curve, including Early Majority, Late Majority, and Laggards (Robinson, 2009) (Rogers, 1981).

Overall, this study’s findings regarding EHR adoption have a relationship to implementation science as well as policy and programs to encourage EHR adoption by physicians for use in their practices. As EHR adoption research becomes more specific in its results about characteristics and predictors of adoption and de-adoption, the opportunity to converge EHR adoption and implementation science grows (Brownson, Colditz, & Proctor, 2012). These two areas, hinged by Rogers’ Theory of the Diffusion of Innovation and other works, are essential to developing insights and knowledge needed to advance implementation of digital capabilities supporting chronic care management for patients with multiple chronic conditions. For example, oncology care management—as with all chronic illness care, fraught with complexities that require careful coordination—can benefit greatly from translating implementation science to EHR adoption practice. Given increases in the incidence of chronic illness and the government’s emphasis



through CMS Medicare and Medicaid programs on digital support for management of these conditions, EHR adoption is essential. Additionally, this creates opportunity for the financial viability of physician practices as CMS launches financial incentives through new reimbursement codes (such as CCM CPT 99490) and others in the telehealth and telemedicine areas, to digitally connect providers with patients using EHR infrastructure as the foundation for coordinating care of chronically ill patients (Sullivan, 2015). As the future of medicine and care coordination evolves, EHR adoption by physicians for use in their practices is at the heart of the way forward.

## References

- Abreu, M. (2006, November 16). *ePharm eXtra: 71M adults on Web for Rx info*. Retrieved January 5, 2011, from Manhattan Research Cybercitizen Health c6.0:  
[http://www.manhattanresearch.com/newsroom/Recent\\_Coverage/11162006\\_71M\\_Adults\\_on\\_Web.aspx](http://www.manhattanresearch.com/newsroom/Recent_Coverage/11162006_71M_Adults_on_Web.aspx)
- AHRQ Project Seeks to Cure What Ails Electronic Health Records*. (2010, July). Retrieved 2011, from AHRQ.org: <http://healthit.ahrq.gov/portal/server.pt?>
- Amatayakul, M. K. (2006). *Electronic Health Records: A Practical Guide for Professional and Organizations, 3rd Edition [Paperback]* (3rd ed.). Chicago, Illinois: AHIMA Press.
- American Academy of Family Physicians. (2014, November 17). *Summary of the 2015 final Medicare physician fee schedule*. Retrieved June 1, 2015, from American Academy of Family Physicians:  
<http://www.aafp.org/dam/AAFP/documents/advocacy/payment/medicare/feesched/ES-2015MPFS-110514.pdf>
- American Medical Association. (2001). *Physician Socioeconomic Statistics, 2000-2002*. Chicago: AMA.
- Andrews, J., Pearch, K., Ireson, C., & Love, M. (2004). Current state of information technology use in a US primary care practice-based research network. *Inform Prim Care* , 12 (1), 11-18.
- Ashish K. Jha, C. M. (2010). A Progress Report on Electronic Health Records in Hospitals. *Health Affairs* , 29 (10), 1951-1957.
- Barlow, K. (2011). *The Complete Guide to Physician Relationships: Strategies for the Accountable Care Era*. Danvers, MA, USA: HealthLeaders Media A Division of H C Pro.
- Bates, D. W. (2005). Physicians And Ambulatory Electronic Health Records. *Health Affairs* , 24 (no. 5), 1180-1189.
- Bernstein, S. W., & Broccolo, B. M. (2006, August 23). *President Bush signs Executive Order promoting Quality and Efficient Health Care through Use of Health Information Technology*. Retrieved November 29, 2011, from McDermott Will & Emery:  
[http://www.mwe.com/index.cfm/fuseaction/publications.htdetail/object\\_id/4d730de6-e3ed-4a06-bba7-98779366ab1d.cfm](http://www.mwe.com/index.cfm/fuseaction/publications.htdetail/object_id/4d730de6-e3ed-4a06-bba7-98779366ab1d.cfm)
- Blackwell, D. L., Lucas, J. W., & Clarke, T. C. (2014). *Summary health statistics for U.S. adults: National Health Interview Survey*. Washington, DC: National Center for Health Statistics.

Bloomrosen, M., Starren, J., Lorenzi, N. M., Ash, J. S., Patel, V. L., & Shortliffe, E. H. (2011). Anticipating and addressing the unintended consequences of health IT and policy: a report from the AMIA 2009 Health Policy Meeting. *J Am Med Inform Assoc.* , 18 (1), 82-90.

Blumenthal, D. M. (2009). Stimulating the Adoption of Health Information Technology. *N Engl J Med* , 360, 15.

Blumenthal, D., & Tavenner, M. (2010). The “Meaningful Use” Regulation for Electronic Health Records. *N Engl J Med* , 501-504.

Boston University School of Public Health. (2013, January 22). *Diffusion of Innovation Theory*. Retrieved May 25, 2015, from Behavioral Change Models: <http://sphweb.bumc.bu.edu/otlt/MPH-Modules/SB/SB721-Models/SB721-Models4.html>

Boston University School of Public Health. (2013, January 22). *Diffusion of Innovation Theory*. Retrieved May 14, 2015, from Behavior Change Models: <http://sphweb.bumc.bu.edu/otlt/MPH-Modules/SB/SB721-Models/SB721-Models4.html>

Brailer, D. (2005, July). Economic Perspectives on Health Information Technology. *Business Economic* , 7-15.

Brownson, R. C., Colditz, G. A., & Proctor, E. K. (Eds.). (2012). *Dissemination and Implementation Research in Health: Translating Science to Practice*. New York, NY: Oxford University Press, Inc.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The Benefits Of Health Information Technology: A Review Of The Recent Literature Shows Predominantly Positive Results. *Health Affairs* , 30 (No. 3), 464-471.

Buntin, M. B., Burke, M. F., Hoaglin, M. C., & Blumenthal, D. (2011). The Benefits Of Health Information Technology: A Review Of The Recent Literature Shows Predominantly Positive Results. *Health Affairs* , 30 (No. 3), 464-471.

Burke-Bebee, S. &. (2008). Assessing EHR Adoption & Implementation in Small Physician Office Settings. *Presentation to WA State Health Information Infrastructure Advisory Board*.

Burt, C. S. (2005). Which Physicians and Practices Are Using Electronic Medical Records? *Health Affairs* , 24 (no. 5), 1334-1343.

Bush, G. (2004). [whitehouse.gov/news/releases](http://www.whitehouse.gov/news/releases). Retrieved January 2011, from whitehouse.gov: <http://www.whitehouse.gov/news/releases/2004/04/20040427-4.html>

Castillo, V., Martinez-Garcia, A., & Pulido, J. (2010). A knowledge-based taxonomy of critical factors for adoption electronic health record systems by physicians: a systematic literature review. *BMC Med Inform Decis Mak* , 10-60.

CBS news story. (2011, February 1). Difficulty Tracing Numerous Prescriptions Can Lead to Patient Dangers.

Center for Studying Health System Change (CTS). (2009). *2008 Health Tracking Physician Survey*. Retrieved February 07, 2011, from CTS: <http://www.hschange.com/index.cgi?file=cts1>

Center for Studying Health System Change. (2003). Community tracking Study Physician Survey, 2000-2001. Washington, DC, United States: Ann Arbor, MI:Inter-university Consortium for Political and Social Research.

Center for Studying Health System Change. (2006). Community tracking Study Physician Survey, 2004-2005. Washington, DC, United States: Ann Arbor, MI:Inter-university Consortium for Political and Social Research, 2008-05-14.

Center for Studying Health System Change. (2011 йил 2-June). *Using the HCS Data Files*. Retrieved 2011 йил 6-June from Center for Studying Health System Change: <http://www.hschange.com/index.cgi?data=11>

Center for Studying Health System Change. (2011, June 2). *Using the HCS Data Files*. Retrieved June 6, 2011, from Center for Studying Health System Change: <http://www.hschange.com/index.cgi?data=11>

Centers for Medicare and Medicaid Services. (2010). Medicare & Medicaid EHR Incentive Program. *EHR Incentive Programs* (pp. 1-33). cms.gov.

Chaudry, B., Wang, J., Wu, S., Maglione, M., Majica, W., Roth, E., et al. (2006). Systematic review: impact of health information technology on quality, efficiency, and costs of medical care. *Ann Intern Med* , 144 (10), 742-52.

Chenghui, L., & West-Strum, D. (2010). Patient Panel of Underserved Populations and Adoption of Electronic Medical Record Systems by Office-Based Physicians. *Health Services Research* , 45 (4).

Choudrhury, A. (2010). *Chronbach's Alpha*. Retrieved 2012 йил 16-April from [www.experiment-resources.com](http://www.experiment-resources.com): <http://www.experiment-resources.com/cronbachs-alpha.html>

Cleary, P. D., & Jette, A. M. (1984). The Validity of Self-reported Physician Utilization Measures. *Medical Care* , 22, 796-803.

CMS Office of Public Affairs. (2010, December 22). *CMS Media Release Database - Press Releases*. Retrieved February 15, 2011, from cms.gov: <http://www.cms.gov/apps/media/press/release.asp>

Cole, L., & Houston, S. (1997). Integrating information technology with an outcomes management program. *Critical Care Nursing Quarterly* , 19 (4), 71-79.

Committee on Data Standards for Patient Safety Institute of Medicine. (2003). *Key Capabilities of an Electronic Health Record System*. Washington, D.C.: The National Academies Press.

Committee on Quality of Health Care in America - Institute of Medicine. (2001). *Crossing the Quality Chasm: A New Health System for the 21st Century*. 2101 Constitution Avenue, N.W. Washington, DC 20418, NATIONAL ACADEMY PRESS . Washington, DC: The National Academy Press.

Committee on Quality of Health Care in America Insitute of Medicine. (1999). *To Err Is Human*. (L. Kohn, J. Corrigan, & M. Donaldson, Eds.) Washington, DC: Nation Academy Press.

Committee on Quality of Health Care in America, Institute of Medicine. (2001). *Crossing the Quality Chasm: A New Health System for the 21st Century*. Washington, DC: National Academy Press.

Cooper, G. F. (2005). Defining a Workable Strategy to Stimulate Widespread Adoption of Electronic Health Records in the United States. *J Am Med Inform Assoc.* , 12 (1), 1-2.

Darlington, R. B. (1991). *Factor Analysis*. Retrieved April 16, 2012, from psych.cornell.edu: <http://www.psych.cornell.edu/darlington/factor.htm>

Daugherty, L. W. (2008). *Health Information Technology-Electronic Health Records: A Primer*. Sacramento, CA: California Research Bureau.

Davis, K., Doty, M. M., Shea, K., & Stremikis, K. (2009). Health Information Technology and Physician Perceptions of Quality of Care and Satisfaction. *Health Policy* , 90 (2-3), 239-246.

Dean, J., Vernon, D., Cook, L., Nechodom, P., Reading, J., & Suruda, A. (2001). Probabalistic Linkage of Computerized Ambulance and Inpatient Hospital Discharge Records: A Potential Tool for Evaluation of Emergency Medical Services. *Annals of Emergency Medicine* , 37 (6), 616-626.

DesRoches, C. M. (2015). Progress and Challenges in Electronic Health Record Adoption: Findings From a National Survey of Physicians. *Ann Intern Med.* , 162 (5), 396.

DesRoches, C. M., Audet, A. M., Painter , M., & Donelan, K. (2013). Meeting Meaningful Use Criteria and Managing Patient Populations A National Survey of Practicing Physicians. *Annals of Internal Medicine* , 158, 791-799.

DesRoches, C., Campbell, E. G., Roa, S. R., Donelan, K., Ferris, T. G., Jha, A., et al. (2008). Electronic Health Records in Ambulatory Care — A National Survey of Physicians. *New England Journal of Medicine* , 359, 50-60.

DesRoches, C., Campbell, E., Rao, S., Donelan, K., Ferris, T., Jha, A., et al. (2008). Electronic Health Records in Ambulatory Care — A National Survey of Physicians. *N Engl J Med* , 50-60.

*Diffusion of Innovations*. (2011, February 16). Retrieved February 16, 2011, from Wikipedia, the free encyclopedia: [http://en.wikipedia.org/wiki/Diffusion\\_of\\_innovations](http://en.wikipedia.org/wiki/Diffusion_of_innovations)

Drazen, E. (2011). *CSC Update of Stage 2 Current Direction and Timing of Meaningful Use Requirements*. Falls Church, Virginia: Computer Sciences Corporation. All rights reserved. WA11\_0195 HCG.

Dvorak, K. (2015, February 15). *CMS extends Meaningful Use attestation deadline for EPs*. Retrieved June 1, 2015, from FierceEMR: <http://www.fierceemr.com/story/cms-extends-meaningful-use-attestation-deadline-eps/2015-02-25>

Einbinder, C., Rury, C., & Safran, C. (1995). Outcomes research using the electronic patient record: Beth Israel Hospital's experience with anticoagulation. *Proceedings of the Annual Symposium of Computer Applications in Medical Care* (pp. 819-23). Boston, MA: Beth Israel Hospital, Harvard Medical School.

Evans, D., Nichol, W., & Perlin, J. (2006). Effect of the implementation of an enterprise-wide Electronic Health Record on productivity in the Veterans Health Administration. *Health Econ Policy Law* , 163-9.

Federal Accounting Standards Advisory Board (FASAB). (2011, June 30). *Standards: Authoritative Source of Guidance*. Retrieved February 21, 2012, from [fasab.gov](http://www.fasab.gov): <http://www.fasab.gov/accounting-standards/authoritative-source-of-gaap/>

Ford, E., Menachemi, N., & Phillips, M. (2006). Predicting the Adoption of Electronic Health Records by Physicians: When Will Health Care be Paperless? *J Am Med Inform Assoc* , 106-112.

Goldman, D. (2009). *Obama's big idea: Digital health records*. Retrieved February 2011, from CNNMoney.com: [http://money.cnn.com/2009/01/12/technology/stimulus\\_health\\_care](http://money.cnn.com/2009/01/12/technology/stimulus_health_care)

Goldzweig, C., Towfigh, A., Maglione, M., & Shekelle, P. (2009). Costs And Benefits Of Health Information Technology: New Trends From The Literature. *Health Affairs* , 28 (2), 282-293.

Grant, R. W., Campbell, E. G., Gruen, R. L., Ferris, T. G., & Blumenthal, D. (2006). Prevalence of Basic Information Technology Use by U.S. Physicians. *J GEN INTERN MED* , 21, 1150-1155.

Grant, R., Campbell, R., Gruen, R., Ferris, T., & Blumenthal, D. (2006, July 17). Prevalence of Basic Information Technology Use by U.S. Physicians. *Journal of General Internal Medicine* , 1150-1155.

Greenhalgh, R., Robert, G., Macfarlane, F., Bate, P., & Kyriakidou, O. (2004). Diffusion of Innovations in Service Organizations: Systematic Review and Recommendations. *Milbank Quarterly* , 581-629.

- Guttman, L. (1953). *Image Theory for the Structure of Quantitative Variables*. Retrieved February 14, 2011, from Factor Analysis Using SAS PROC FACTOR: <http://www.utexas.edu/cc/docs/stat53.html#fn>
- Hammer, M., & Champy, J. (2001). *Reengineering the Corporation - A manifesto for Business Revolution*. New York, NY: HarperCollins.
- HIMSS Analytics. (2011). *U.S. EMR Adoption ModelSM Trends*. HIMSS Analytics.
- Hing, E., & Burt, C. (2007, March). Office-based medical practices: methods and estimates from the national ambulatory medical care survey. *Adv Data* , 1-15.
- Hing, E., & Hsiou, C. *Electronic Health Record Use by Office-based Physicians and their Practices: United States, 2007*. Natl Health Stat Report. 2010 Mar 31;(23):1-11.
- Hing, E., & Hsiou, C. (2007). *Electronic Health Record Use by Office-based Physicians and their Practices: United States, 2007*. Natl Health Stat Report. 2010 Mar 31;(23):1-11.
- Hing, E., & Uddin, S. (2010, October). *NCHS Data Brief No. 47: Visits to Primary Care Delivery Sites: United States, 2008*. Retrieved February 15, 2011, from cdc.gov: <http://www.cdc.gov/nchs/data/databriefs/db47.pdf>
- Hing, E., Burt, C., & Woodwell, D. (2007). *Electronic Medical Record Use by Office-based Physicians and Their Practices: United States, 2006*. National Center for Health Statistics. Hyattsville, MD: DHHS .
- Hing, E., Burt, C., & Woodwell, D. (2007). *Electronic Medical Record Use by Office-Based Physicians and Their Practices: United States, 2006*. U.S. DEPARTMENT OF HEALTH AND HUMAN SERVICES. Centers for Disease Control and Prevention.
- Hirsch, M. D. (2015, May 6). *Not all EHR research can be taken at face value*. Retrieved May 2015, from FierceEMR: <http://www.fierceemr.com/story/not-all-ehr-research-can-be-taken-face-value/2015-05-06>
- HITC Staff. (2015, 1 7). *55% of Physicians Will Not Attest to Meaningful Use Stage 2 This Year*. Retrieved May 3, 2015, from HIT Consultant: <http://hitconsultant.net/2015/01/07/55-of-physicians-will-not-attest-to-meaningful-use-stage-2-this-year/>
- HITC Staff. (2015, 1 7). *55% of Physicians Will Not Attest to Meaningful Use Stage 2 This Year*. Retrieved 2015, from HIT Consultant: <http://hitconsultant.net/2015/01/07/55-of-physicians-will-not-attest-to-meaningful-use-stage-2-this-year/>
- Hsiao, C.-J., Hing, E., & Ashman, J. (2014). *Trends in Electronic Health Record System Use Among Office-based Physicians: United States, 2007-2012*. Hyattsville, MD: National Center for Health Statistics.

- Hsiao, C.-J., Hing, E., Socey, T. C., & Cai, B. (2010, December). *Electronic Medical Record/Electronic Health Record Systems of Office-based Systems: United States 2009 and Preliminary 2010 State Estimates*. Retrieved May 2015, from CDC National Center for Health Statistics: [http://www.cdc.gov/nchs/data/hestat/emr\\_ehr\\_09/emr\\_ehr\\_09.pdf](http://www.cdc.gov/nchs/data/hestat/emr_ehr_09/emr_ehr_09.pdf)
- Hsu, J. (2008). *Impact of Health Information Technology on Clinical Care*. AHRQ.
- ICPSR. (2015, May). *Find & Analyze Data - Community Tracking Study Series*. Retrieved from ICPSR: <https://www.icpsr.umich.edu/icpsrweb/ICPSR/series/161>
- ICPSR. (2011, June). *Find & Analyze Data*. Retrieved June 6, 2011, from ICPSR: <http://www.icpsr.umich.edu/icpsrweb/ICPSR/ssvd/studies/03820/datasets/0001/variables/PRCTYPE?paging.startRow=26>
- ICPSR. (2011, June 6, 2011). *ICPSR Find and Analyze Data*. Retrieved 2010, from Inter-university Consortium for Political and Social Research (ICPSR): <http://www.icpsr.umich.edu/icpsrweb/ICPSR/studies/3820/detail>, accessed 2010
- Innovation adoption curve of Rogers*. (2009, Jan 7). Retrieved January 2009, from Value Based Management.net: [http://www.valuebasedmanagement.net/methods\\_rogers\\_innovation\\_adoption\\_curve.html](http://www.valuebasedmanagement.net/methods_rogers_innovation_adoption_curve.html)
- Institute of Medicine. (2003). *Key Capabilities of an Electronic Health Record System*. Institute of Medicine, Committee on Data Standards for Patient Safety - Board on Health Care Services. Washington, D.C.: National Academy Press.
- Institute of Medicine. (1991). *The computer-based patient record: an essential technology for health care*. Washington, DC: National Academy Press.
- Institutes of Medicine Committee on Patient Safety and Health Information Technology. (2012). *Health IT and Patient Safety: Building Safer Systems for Better Care*. Institutes of Medicine. Washington D.C.: The National Academies Press.
- Jamoom, E., Beatty, P., Bercovitz, A., Woodwell, D., Palso, K., & Rechtsteiner, E. (2012, July). *Physician Adoption of Electronic Health Record Systems: United States, 2011*. Retrieved from Centers for Disease Control and Prevention NCHS Data Brief: <http://www.cdc.gov/nchs/data/databriefs/db98.htm>
- Jao, J. (2015, June 1). *Customer Retention Should Outweigh Customer Acquisition*. (Adobe, Ed.) Retrieved from CMO: [http://www.cmo.com/articles/2013/7/18/customer\\_retention.html](http://www.cmo.com/articles/2013/7/18/customer_retention.html)
- Jha, A. J., DesRoches, C. M., Kralovec, P. D., & Joshi, M. S. (2010). A Progress Report On Electronic Health Records In U.S. Hospitals. *Health Affairs* .



- Jha, A. K., DesRoches, C. M., Campbell, E. G., Donelan, K., Rao, S. R., Ferris, T. G., et al. (2009, March 29). Use of Electronic Health Records in U.S. Hospitals. *The New England Journal of Medicine* , 360, pp. 1628-38.
- Jha, A. K., DesRoches, C. M., Kravolec, P. D., & Joshi, M. S. (2010). A Progress Report On Electronic Health Records In U.S. Hospitals. *Health Affairs* , 29 (10), 1377.
- Jha, A., Herreris, T., Donelan, K., DesRoches, C., Shields, A., Rosenbaum, S., et al. (2006). How Common Are Electronic Health Records In The United States? A Summary Of The Evidence. *Health Affairs* , w496-w507.
- Jha, A., Poon, E., Bates, D., Blumenthal, D., Middleton, B., Kuperman, G., et al. (2003). Defining the Priorities and Challenges for the Adoption of Information Technology in HealthCare: Opinions from an Expert Panel. (p. 881). Annual Symposium Proceedings Archive.
- Johnson, T. K. (2009). *Ambulatory Care Stands Out Under Reform*. Retrieved February 15, 2011, from HFMA.org: <http://www.hfma.org/Templates/Print.aspx?id=20421>
- Kern, L. M., Barron, Y., Kaushal, R., & Dhopeswarkar, R. V. (2012). Health Information Exchange and Ambulatory Quality of Care. *Applied Clinical Informatics* , 3 (2), 197-209.
- Kern, L. M., Wilcox, A., Shapiro, J., Shopeshwarkar, R. V., & Kaushal, R. (2012). Which Components of Health Information Technology Will Drive Financial Value? *The American Journal of Managed Care* , 18 ((8)), 438-445.
- Ketcham, J. B. (2007). Physician Practice Size And Variations in Treatments And Outcomes: Evidence From Medicare Patients With AMI. *Health Affairs* , 26 (1), 195- 205.
- Kovach, C., Morgan, S., Noonan, P., & Brondino, M. (2008). Using Principles of Diffusion of Innovation to Improve Nursing Home Care. *Journal of Nursing Care Quality* , 23 (2), 132-139.
- Lee, T.-T. (2004, November). Application of Rogers' innovation-diffusion model. *Applied Nursing Research* , 231-238.
- Li, C. (2011). Use of Health Information Technology by Office-based Physicians: Comparison of Two Contemporaneous Public-Use Physiican Surveys. *Perspectives in Health Information Management* , 8 (Fall).
- Loomis, G., Ries, J., Saywell, R., & Thakker, N. (2002). If electronic medical records are so great, why aren't family physicians using them? *Journal of Family Practice* , 636-641.
- Mattocks, K., Lalime, K., Tate, J., Giannotti, T., Carr, K., Carrabba, A., et al. (2007). The state of physician office-based health information technology in Conneticut: current use, barriers and future plans. *Conn Med* , 71 (5), 313.

- McDowell, M. H., & McKaughan, M. (2015, January 12). *Studying Physicians' Use of Electronic Health Records-and Their Benefits*. Retrieved 2015, from Robert Wood Johnson Foundation-Program Results Report Brief Grant ID: 68812.
- McKesson. (2102, August 31). *McKesson Provider Technologies*. Retrieved August 31, 2012, from MeKesson.com:  
[http://www.mckesson.com/en\\_us/McKesson.com/Our%2BBusinesses/McKesson%2BProvider%2BTechnologies/Products%2Band%2BServices/Products%2Band%2BServices.html](http://www.mckesson.com/en_us/McKesson.com/Our%2BBusinesses/McKesson%2BProvider%2BTechnologies/Products%2Band%2BServices/Products%2Band%2BServices.html)
- Menachemi, N. (2006). Barriers to ambulatory EHR: who are 'imminent adopters' and how do they differ from other physicians? *Informatics in Primary Care*, 14 (2), 101-108(8).
- Menachemi, N., & Brooks, R. (2006). EHR and Other IT Adoption among Physicians: Results of a Large-Scale Statewide Analysis. *Journal of Healthcare Information Management*, 20 (3), 79-87.
- Merriam-Webster Dictionary. (2012, 09 09). *Iatrogenesis - Medical Definition and more from Merriam-Webster*. Retrieved 09 09, 2012, from Merriam-webster.com: <http://www.merriam-webster.com/medical/iatrogenesis>
- Middleton, B., Hammond, E., Brennan, P., & Cooper, G. (2005). Accelerating U.S. EHR Adoption: How to Get There From Here. Recommendations Based on the 2004 ACMI Retreat. *J Am Med Inform Assoc*, 12 (1), 13-19.
- Miller, R. H., West, C., Brown, T. M., Sim, I., & Ganchoff, C. (2005). The Value Of Electronic Health Records In Solo Or Small Group Practices. *Health Affairs*, 24 (5), 1127-1137.
- Miller, R. H., West, C., Brown, T. M., Sim, I., & Ganchoff, C. (2005). The Value Of Electronic Health Records In Solo Or Small Group Practices. *Health Affairs*, 24 (No. 5), 1127-1137.
- Monegain, B. (2004). *Brailer to outline nation's healthcare IT plan*. Healthcare IT News .
- Morton, M. (2009). A Framework for Predicting EHR Adoption Attitudes: A Physician Survey. *Perspectives in Health Information Management*, 6(Fall).
- Networks, H. &. (2012, August 31). *Most Wired - Are You Most Wired?* Retrieved August 31, 2012, from Most Wired: <http://www.hhnmostwired.com/hhnmostwired/index.jsp>
- News Staff. (2015, April 14). *CMS Clarifies Use of CCM Code in Medicare Advantage Plans*. Retrieved from AAFP: [http://www.aafp.org/news/practice-professional-issues/20150414ccmguidance.html#.VS3T\\_kTOH4.yahoomail](http://www.aafp.org/news/practice-professional-issues/20150414ccmguidance.html#.VS3T_kTOH4.yahoomail)
- Obama jobs creation and electronic medical records in healthcare*. (2009, January 20). Retrieved 2010, from forbes.com.

Obama, P. B. (2009, February 24). *Address to Joint Session of Congress*. Retrieved February 15, 2011, from whitehouse.gov: [http://www.whitehouse.gov/the\\_press\\_office/Remarks-of-President-Barack-Obama-Address-to-Joint-Session-of-Congress/](http://www.whitehouse.gov/the_press_office/Remarks-of-President-Barack-Obama-Address-to-Joint-Session-of-Congress/)

Office of the National Coordinator. (2010, May 25). *Measuring Health IT Adoption*. Retrieved January 27, 2011, from HealthIT.hhs.gov: <http://healthit.hhs.gov/portal/server.pt?>

O'Malley, A. S., Grossman, J. M., Cohen, G. R., Kemper, N. M., & Pham, H. H. (2009, December 29). Are Electronic Medical Records Helpful for Care Coordination? Experiences of Physician Practices. *Journal of General Internal Medicine* .

Orders, G. W. (2011, July 23). *Executive Orders of George W. Bush (January 20, 2001 - January 20, 2009)*. Retrieved November 29, 2011, from Wikisource: [http://en.wikisource.org/wiki/Author:George\\_W.\\_Bush/Executive\\_orders](http://en.wikisource.org/wiki/Author:George_W._Bush/Executive_orders)

Orszag, P. R. (2008, May). *Evidence on the Costs and Benefits of Health Information Technology*. Retrieved January 17, 2012, from cbo.gov: <http://www.cbo.gov/ftpdocs/91xx/doc9168/maintext.3.1.shtml>

Pawson, D., Greenhalgh, P., DG, H., & Walshe, K. (2005). Realist Synthesis: an Approach to Synthesising Research Evidence on Complex Social Interventions for Policymakers and Managers. *Journal of Health Services Research Policy* , 10 (1), 21-34.

Pennic, F. (2014, July 20). *Survey: 22% of Physicians Are Opting Out of Meaningful Use*. Retrieved from HIT Consultant: <http://hitconsultant.net/2014/07/20/survey-22-of-physicians-are-opting-out-of-meaningful-use/>

Porter, M. (2013, February). *Adoption of Electronic Health Records in the United States*. Retrieved from Kaiser Permanente International [kp.org/international](http://www.kp.org/international): <https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=4&ved=0CDsQFjAD&url=https%3A%2F%2Fxnnet.kp.org%2Fkpinternational%2Fdocs%2FAAdoption%2520of%2520Electronic%2520Health%2520Records%2520in%2520the%2520United%2520States.pdf&ei=sddGVeSxGo6zogTPvoDwBA>

Rao, S. R., DesRoches, C. M., Donelan, K., Campbell, E. G., Miralles, P. D., & Jha, A. K. (2011). Electronic health records in small physician practices: availability, use, and perceived benefits. *J Am Med Inform Assoc.* ; : . , 18 ((3)), 271–275.

Rao, S. R., DesRoches, C. M., Donelan, K., Campbell, E. G., Miralles, P. D., & Jha, A. K. (2011). Electronic health records in small physician practices: availability, use, and perceived benefits. *J Am Med Inform Assoc.* , 18 ((3)), 271–275.

Reed, M. C., & Grossman, J. M. (2004). *Limited Information Technology for Patient Care in Physician Offices*. Washington D.C.: Center for Studying Health System Change.

- Reed, M., & Grossman, J. (2004). *Limited information technology for patient care in physician offices*. Center for Studying Health System Change.
- Robert Wood Johnson Foundation. (2008, June 18). *Physician Adoption of Electronic Health Records Still Extremely Low, But Medicine May be at a Tipping Point*. Retrieved February 17, 2011, from RWJF.org: <http://www.rwjf.org/coverage/product.jsp?id=31632>
- Robert Wood Johnson Foundation; George Washington University Medical Center; Institute for Health Policy. (2006). *Health Information Technology in the United States: The Information Base for Progress*. Robert Wood Johnson Foundation.
- Robinson, L. (2009, Jan). *A summary of Diffusion of Innovations*. Retrieved May 2015, from Enabling Change: [http://enablingchange.com.au/Summary\\_Diffusion\\_Theory.pdf](http://enablingchange.com.au/Summary_Diffusion_Theory.pdf)
- Rogers, E. (1981). *Diffusion of Innovations*. New York, London, Toronto, Sydney, Tokyo, Singapore: The Free Press.
- Rose, S. (2005). *Econometric Approaches to Causal Inference: Graduate Methods Master Class*. [rtm.wustl.edu/GMMC/SRoseGMMC.ppt](http://rtm.wustl.edu/GMMC/SRoseGMMC.ppt). Harvard University.
- Santos, J. R. (1999, April ). *Cronbach's Alpha: A Tool for Assessing the Reliability of Scales*. Retrieved from Extension Journal, Inc.: <http://www.joe.org/joe/1999april/tt3.php/>
- Shilling, B. (2011, June/July). *Quality Matters*. Retrieved May 25, 2015, from The Commonwealth Fund Innovations in Health Care Quality Improvement: <http://www.commonwealthfund.org/publications/newsletters/quality-matters/2011/june-july-2011/in-focus>
- Steed, R. (2014). *CMS to pay health care providers to participate in digital health*. Retrieved 2014, from Digital Health: <https://www.linkedin.com/grp/post/2181454-5935215511297085442>
- Sullivan, T. (2015, May 27). *Innovation Pulse: Meet the new CMS code worth \$17 billion annually*. Retrieved May 30, 2015, from Healthcare IT News: <http://m.healthcareitnews.com/news/innovation-pulse-meet-new-cms-code-worth-17-billion-annually>
- The Commonwealth Fund. (2009, December 29). *Are Electronic Medical Records Helpful for Care Coordination? Experiences of Physician Practices*. *Journal of General Internal Medicine* .
- The International Council on Medical and Care Computetics. (2006, November 30). *Correlates of Electronic Health Record Adoption In Office Practices*. Retrieved February 11, 2011, from ICMCC Science Pages: <http://science.icmcc.org/2006/11/30/correlates-of-electronic-health-adoption-in-office-practices>
- The Lewin Group. (2005). *HEALTH INFORMATION Technology Leadership Panel*.

Thompson, T. G., & Brailer, D. J. (2004, July 21). *The Decade of Health Information Technology: Delivering Consumer-centric and Information-rich Health Care - Framework for Strategic Action*. Retrieved November 29, 2011, from Providersedge.com/ehdocs/ehr: [http://www.providersedge.com/ehdocs/ehr\\_articles/The\\_Decade\\_of\\_HIT-Delivering\\_Customer-centric\\_and\\_Info-rich\\_HC.pdf](http://www.providersedge.com/ehdocs/ehr_articles/The_Decade_of_HIT-Delivering_Customer-centric_and_Info-rich_HC.pdf)

Trochim, W. M. (2008, 10 20). *Guttman Scaling*. Retrieved 2013, from Web Center for Social Research Methods-Research Methods Knowledge Base: <http://www.socialresearchmethods.net/kb/scalgutt.php>

Tungsten. (2009, December 10). *Diffusion of Innovations according to Rogers (1962)*. Retrieved February 16, 2011, from Wikipedia, the free encyclopedia: <http://en.wikipedia.org/wiki/File:Diffusionofideas.PNG>

UCLA Academic Technology Services, Statistical Consulting Group. (2009). *Factor Analysis*. Retrieved February 14, 2011, from UCLA Academic Technology Services: [http://www.ats.ucla.edu/stat/sas/library/factor\\_ut.htm](http://www.ats.ucla.edu/stat/sas/library/factor_ut.htm)

UCLA Academic Technology Services, Statistical Consulting Group. (2009). *Stata Annotated Output: Factor Analysis*. Retrieved February 11, 2011, from UCLA Academic Technology Services: [http://www.ats.ucla.edu/stat/stata/output/fa\\_output.htm](http://www.ats.ucla.edu/stat/stata/output/fa_output.htm)

UCLA: Academic Technology Services, Statistical Consulting Group. (2009). *SPSS FAQ: What does Cronbach's alpha mean?* Retrieved February 11, 2011, from UCLA Academic Technology Services: <http://www.ats.ucla.edu/stat/spss/faq/alpha/html>

US Department of Health and Human Services. (2009, February 17). *HITECH Act Enforcement Interim Final Rule*. Retrieved February 3, 2011, from United States Department of Health and Human Services hhs.gov: <http://www.hhs.gov/ocr/privacy/hipaa/administrative/enforcementrule/hitech/enforcementiffr.html>

USLegal. (2015). *Benefit-of-the-Bargain Rule Law & Legal Definition*. Retrieved June 1, 2015, from USLegal Definitions: <http://definitions.uslegal.com/b/benefit-of-the-bargain-rule/>

Wicklund, E. (2013, July 12). Retrieved 2014, from mHealthNews: <http://www.mhealthnews.com/news/ata-voices-cautious-support-cms-proposals-expand-telemedicine?page=1>

Wicklund, E. (2014, November 3). *CMS boosts telehealth in 2015 physician pay schedule*. Retrieved May 30, 2015, from mHealthNews: <http://www.mhealthnews.com/news/cms-boosts-telehealth-2015-physician-pay-schedule>

Wicklund, E. (2014, October 22). *CMS urged to reimburse docs for mHealth diabetes tools*. Retrieved 2014, from mHealthNews: <http://www.mhealthnews.com/news/cms-urged-reimburse-docs-mhealth-diabetes-tools>

Yee, T. (2010). *The Impact and Long-Term Sustainability of Nursing Process Improvements Experiences from Transforming Care at the Bedside*. University of California at Los Angeles, Health Services.