<u>TESTING THEORIES OF INNOVATION DIFFUSION: ANALYSIS OF PHYSICIANS' ADOPTION OF ELECTRONIC HEALTH RECORDS</u>

by

Martin F. Cohen
A Dissertation
Submitted to the
Graduate Faculty
of
George Mason University
in Partial Fulfillment of
The Requirements for the Degree
of
Doctor of Philosophy
Public Policy

Committee:

_______________________________________ David M. Hart, Chair

_______________________________________ Laurie Schintler

_______________________________________ Lorens A. Helmchen

Fredric Blavin, External Reader

_______________________________________ Kenneth J. Button, Program Director

_______________________________________ Mark J. Rozell, Dean

Date: __________________________________ Summer Semester 2015
George Mason University
Fairfax, VA

Testing Theories of Innovation Diffusion: Analysis of Physicians' Adoption of Electronic Health Records

A Dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy at George Mason University

by

Martin F. Cohen
Master of Public Administration
Harvard University, 1992
Bachelor of Arts
Harvard College, 1986

Director: David M. Hart, Professor
School of Policy, Government, and International Affairs

Summer Semester 2015
George Mason University
Fairfax, VA

Dedication

This is dedicated to my wife, Maureen, our children, Matt, Rachel, and Sam, and my parents, Ben and Eva Cohen. Thanks for your encouragement and the many ways you helped me make it through this process.

Acknowledgements

I owe deep thanks to my Chair, Professor David Hart, for guiding me with excellent comments and support on both the substance and process of this effort. You kept me moving forward and provided exactly the help I needed at several points along the way. Professors Laurie Schintler and Lorens Helmchen also provided very helpful comments and encouragement for which I am most appreciative. I also thank Fredric Blavin for graciously sharing his time and expertise in serving as the External Reader. I thank Bob Krasowski and the Research Data Center (RDC) within the National Center for Health Statistics (NCHS) for facilitating my access to the Physician Workflow survey data, although the findings and conclusions in this study are solely my own and do not represent the views of the RDC, NCHS, or the Centers for Disease Control and Prevention. Finally, I thank my colleagues and friends at Kennell and Associates, especially Dave Kennell, for the steady support and flexibility that allowed me to balance academic and professional demands throughout my PhD program.

Table Of Contents

List Of Tables

List Of Figures

Abstract

TESTING THEORIES OF INNOVATION DIFFUSION: ANALYSIS OF PHYSICIANS' ADOPTION OF ELECTRONIC HEALTH RECORDS

Martin F. Cohen, Ph.D.

George Mason University, 2015

Dissertation Director: Dr. David M. Hart

The Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009 authorized numerous federal programs intended to address barriers to adoption of electronic health records (EHRs). This dissertation analyzes national survey data to test and compare the significance of five factors in physician decisions on whether to adopt an EHR: improved information, the cost of adoption, the HITECH financial incentives program, challenges in selecting a specific EHR vendor or product, and operational implementation barriers. This study focuses on physicians in smaller, physician-owned practices, who are an important target of policies to promote EHR adoption. In addition to the traditional binary analysis of adopters versus non-adopters, this research also tests models with three categories of adoption status: 1) using an EHR, 2) in the process of adoption, and 3) not yet in the process of adoption. Key findings include:

- the degree of importance physicians attach to the HITECH financial incentives is a strong predictor of recent EHR adoption decisions;

- physicians who reported improved information as influential to their decision on whether to adopt an EHR were less likely to have adopted by 2011; and
- in contrast to what the literature on diffusion of network technologies would predict, a majority of physicians have now adopted EHRs despite a lack of meaningful interoperability or market convergence on a dominant design.

The first two findings suggest that both financial incentives and information support should be key components of federal efforts to promote broad physician adoption of other complex innovations. The third finding merits future research to determine whether physicians to date have not actually placed a high value on EHR interoperability, or whether many physicians, at the time of adoption, had poor information on the limited extent of interoperability.

Chapter 1. Introduction

The U.S. health care system is in the midst of integrating information technology (IT) into the clinical delivery of health care. Diffusion of electronic health record (EHR) technology among physicians will likely have widespread ramifications throughout the health care system because physician decisions and actions influence much of the overall cost and quality of health care.[1] This dissertation analyzes national survey data to assess which types of facilitators or barriers reported by U.S. physicians in small, physician-owned practices are most significant in predicting physicians' EHR adoption status.

In addition to its value for refining ongoing federal policies to promote adoption of health IT, an improved understanding of physician decisions on adoption of a complex innovation such as an EHR system is important at a time when policy-makers are increasingly looking to physicians to adopt numerous other ambitious innovations in health care delivery and financing. Beyond this interest from a health policy perspective, analysis of EHR adoption among physicians also offers a contemporary opportunity to assess issues of interest in the broader literature on diffusion of innovation.

[1] While health IT can include other technologies besides EHR systems, in many contexts health IT refers to an EHR system and in this dissertation the two terms are used interchangeably unless otherwise noted.

1.1 What problem is health IT intended to solve?

Proponents of health IT theorize that its broad adoption would improve the efficiency and quality of care delivered in the U.S. health system. Relative to other wealthy nations, the inefficiency of the U.S. health care system is exemplified by an extremely high per capita cost in return for modest performance on a wide range of system-level quality measures (Hillestad et al. 2005, 1103). Figure 1 illustrates that the U.S. is an outlier among wealthy nations with respect to health care expenditures per capita (Organization for Economic Cooperation and Development 2015).

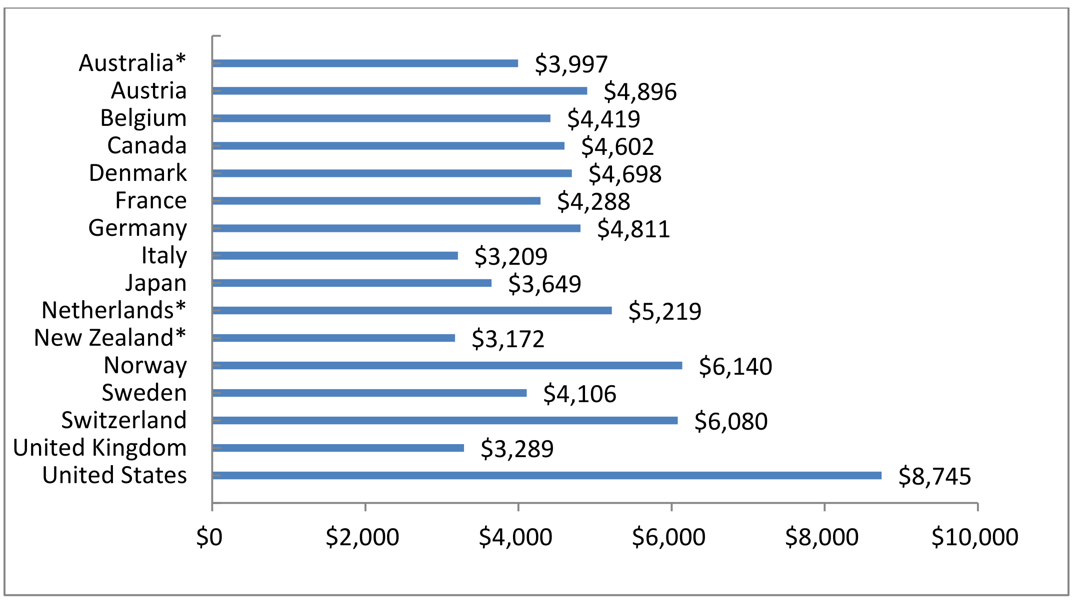

Figure 1. National Health Care Expenditures Per Capita, 2012

* 2011 data.

Source: OECD Health Data: Total Expenditure per Capita, US Dollars Purchasing Power Parity, stats.oecd.org, accessed April 5, 2015. For a description of purchasing power parity, see www.oecd.org/std/ppp.

Meanwhile, although quality is more difficult to measure than expenditures at the level of a national health system, on many quality metrics the U.S. falls in the middle of the pack among wealthy nations (The Commonwealth Fund Commission on a High Performance Health System 2011). While the high cost of American health care has been recognized for decades, concern about the quality obtained for that level of expenditure became a particularly salient issue after a 2001 report issued by the Institute of Medicine (IOM). The IOM (2001, ES1) voiced a critique that still resonates today:

> The American health care system is in need of fundamental change. Many patients, doctors, nurses, and health care leaders are concerned that the care delivered is not, essentially, the care we should receive. . . . Quality problems are everywhere. Between the health care we have and the care we could have lies not just a gap, but a chasm.

One of the specific issues identified by the IOM was the lack of information technology in the delivery of health care, as the IOM (2001, ES4) lamented that physicians and other medical providers typically "operate as silos, often providing care without the benefit of complete information about the patient's condition, medical history, services provided in other settings, or medications prescribed by other clinicians." The IOM's concerns regarding clinicians' lack of patient history and medication information in an EHR were particularly salient coming on the heels of a prior IOM report (1999), focused on patient safety, that estimated that tens of thousands of American deaths each year are caused by preventable medical errors.

In addition to the IOM's general argument that EHRs would improve health care quality, in 2005 the RAND Corporation estimated that full, effective adoption of health IT would ultimately save more than $80 billion per year if accompanied by complementary innovations to identify and reward high-quality, efficient health care providers (Girosi, Meili, and Scoville 2005; Hillestad et al. 2005; R. Taylor et al. 2005). RAND also estimated that EHR adoption could lower age-adjusted mortality rates by 18% and annual employee sick days by 40 million (R. Taylor et al. 2005).

The Congressional Budget Office (2008) has also summarized many specific ways in which EHRs potentially could improve health care quality and efficiency:

- eliminating the cost of medical transcription of a physician's notes on a patient;
- eliminating the cost of maintaining and pulling medical charts from paper files;
- eliminating errors associated with illegible hand-written treatment orders or drug prescriptions, through Computerized Physician Order Entry (CPOE);
- alerting clinicians to consider a less costly prescription drug option;
- alerting clinicians to an adverse drug interaction or allergy for a given patient;
- reducing duplicative laboratory tests or imaging procedures;
- alerting physicians when a patient is due for relevant preventive services (e.g., a flu shot, or a cancer screening such as a mammogram or colonoscopy); and
- improving care coordination for patients with chronic or complex conditions, who often require services provided by multiple clinicians over an extended period.

Over the longer term, an even larger benefit is that EHRs could enable collection of rich patient-level data to study which alternative treatments of a given disease are most effective for different types of patients – known as comparative effectiveness research (CER). EHRs could also enable automated dissemination of relevant CER findings back to clinicians, in what Etheridge (2010) has termed a "rapid-learning" health care system.

1.2 Barriers to EHR adoption and the federal policy response

Despite these many theorized benefits of health IT, however, diffusion of EHRs in the U.S. has been slow (Christensen and Remler 2009; Fonkych and Taylor 2005). Figure 2 shows a gradual rise in physician adoption of EHRs from a low level a decade earlier. Still, as of 2013, less than half of office-based physicians were using an EHR with the set of capabilities that the health IT literature refers to as a "basic EHR" for physicians, and 22% of office-based physicians were not using any type of EHR (Hsiao and Hing 2014).

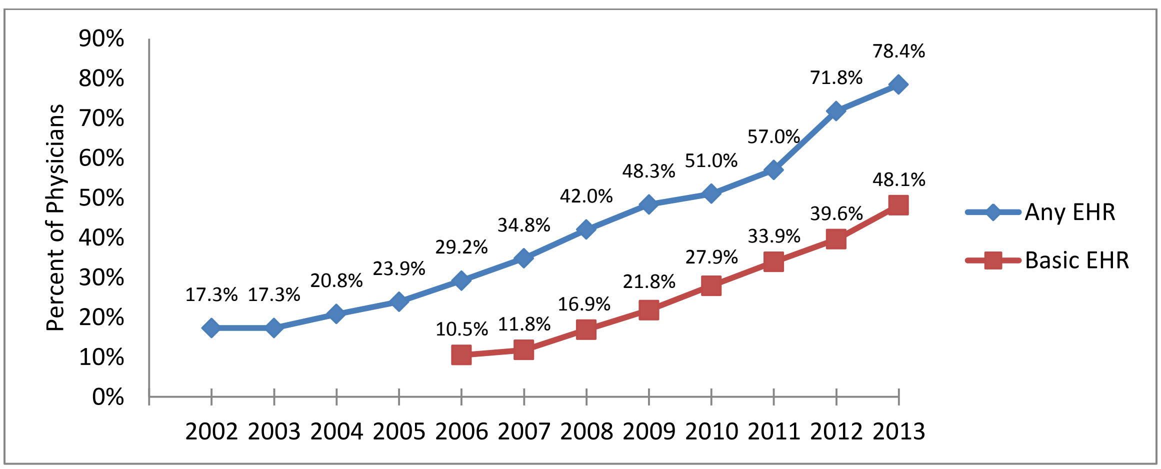

Figure 2. Adoption of EHRs by Office-Based Physicians in the United States

Notes: A "basic EHR" for physicians includes functionality for patient history and demographics, patient problem lists, clinical notes, patient medication and allergy lists, documentation of prescription drug orders, and electronic access to laboratory and imaging results.

Source: Hsiao C and Hing E, "Use and Characteristics of Electronic Health Record Systems Among Office-based Physician Practices: United States, 2001-2013," National Center for Health Statistics, 2014.

While not a focus of this dissertation, EHR adoption among U.S. hospitals has also been slow, although rising in recent years. As of 2013, only 59% of non-federal acute care hospitals in the U.S. had adopted an EHR with the range of functionality that the health IT literature refers to as a "basic EHR" for hospitals (Charles, Gabriel, and Furukawa 2014).

As discussed at greater length in Chapter 2, the health policy literature has generally attributed this slow diffusion of EHRs in the U.S. to a range of adoption barriers, including:

- the financial costs of adoption (Miller et al. 2005; Fleming et al. 2011);
- a poor return on investment due to misaligned incentives (Kleinke 2005; Congressional Budget Office 2008; Christensen and Remler 2009);
- challenges in selecting a specific vendor and the associated fear of product obsolescence, driven in part by lack of interoperability[2] (Blumenthal et al. 2006, 46; Christensen and Remler 2009); and
- implementation concerns due to the complexity of EHR technology (Kellermann and Jones 2013; Blavin et al. 2013; Friedberg et al. 2013; Fernandopulle and Patel 2010).

These specific barriers to health IT adoption in turn fit within several broader theories in the academic literature on diffusion of innovation. The flow of information about an innovation can affect its diffusion through multiple mechanisms. Potential adopters may differ in their basic awareness of an innovation, they may be aware of it but

[2] A key type of interoperability would be a routine capability for different EHR systems to electronically exchange and integrate patients' clinical data.

have not been persuaded to adopt, they may be willing to adopt but lack sufficient information to select among competing product designs, or they may lack the expertise needed for operational implementation of a complex technology (Ryan and Gross 1943; Coleman, Katz, and Menzel 1966; Burt 1987; Rogers 2003; Angst et al. 2010). Financial incentives can influence diffusion because the benefits and costs of adoption can vary across individuals, due to their different circumstances, or over time, due to continual improvements in the technology or reductions in its cost (Griliches 1957; Ruttan 2001, 154; Rosenberg 1972). With complex innovations, the cost of adoption is often largely incurred up front as a sunk cost while the benefits may accrue gradually – a timing issue that couples with imperfect information to delay decisions on adoption (Hall 2005, 466; Stoneman 2002, 8).

Delaying adoption is a particularly relevant choice in the case of network technologies, which include information and communication technology such as EHRs. Network technologies require interoperability, which in turn requires standards. Even a potential adopter who believes there are net benefits to a new network technology may delay adoption to avoid the risk of selecting a product version that will become obsolete if it does not meet subsequent standards for interoperability (Geroski 2000; Stoneman 2002, 8).

In recognition of the multiple barriers to adoption cited in the health IT literature, in February 2009 Congress passed the Health Information Technology for Economic and Clinical Health (HITECH) Act as part of the American Recovery and Reinvestment Act.

As described in more detail in Chapter 4, the HITECH Act includes numerous programs intended to address the major barriers to adoption identified in prior research, including:

- a program of positive and negative financial incentives to improve the benefit-cost ratio for EHR adoption among physicians and hospitals;
- establishment of Regional Extension Centers (RECs) in every state to provide expertise for EHR selection and implementation; and
- government certification of EHR systems that meet the regulatory standards defining Meaningful Use of an EHR, for purposes of the incentives program.

1.3 The research question and its importance

Existing research has identified various objective physician characteristics that are associated with EHR adoption status (Decker, Jamoom, and Sisk 2012; Hsiao, Hing, and Ashman 2014). For example, larger physician practices are more likely to adopt than smaller practices, and practices owned by vertically-integrated organizations such as health maintenance organizations (HMOs) are more likely to adopt than physician-owned practices (Hsiao, Hing, and Ashman 2014). As noted above, there has also been prior research on physicians' concerns about EHR adoption, but those studies that have included quantitative data primarily report straightforward percentages of physicians who cite various issues as barriers to adoption, including two recent studies that reported such tabulations distinctly for adopters and non-adopters (Jamoom et al. 2014; Heisey-Grove and Patel 2014). What is missing from the existing literature is an attempt to systematically quantify and compare the extent to which physicians' views on different factors influencing adoption help to explain their status as EHR adopters or non-adopters.

As one example, in prior research the cost of EHRs is routinely cited as a barrier to adoption, but to what extent do physicians' concerns about the cost of EHR adoption predict who becomes an adopter and who does not? Similarly, while prior research has identified fear of product obsolescence as a barrier to adoption, to what extent does this concern predict adoption status?

Another characteristic of most prior studies of physicians' views on factors influencing EHR adoption is that they have generally reported on the broader, overall population of U.S. physicians, whereas this dissertation focuses on physicians in smaller, physician-owned practices. This narrower focus is valuable for two reasons. First, as discussed in Chapter 3's review of relevant issues from the survey methods literature, this sub-population reflects physicians who are likely to be knowledgeable about decision-making in their practice, given that an EHR adoption decision is likely made for the practice as a whole rather than by each individual physician. Second, this sub-population of physicians is an important target for diffusion policies because, as noted above, their rate of EHR adoption has lagged their counterparts working in large practices or practices owned by larger organizations.

Therefore, this dissertation adds to existing research by drawing upon a nationwide survey of physicians to answer the following research question:

- *Among small, physician-owned practices in the U.S., to what extent is EHR adoption status predicted by physician views on each of the following five factors: improved information, the HITECH financial incentives program, challenges in* *selecting a specific EHR product or vendor, the direct financial cost of adoption, and operational implementation concerns?*

To answer this question, the methodology described in Chapter 3 involved first constructing a set of composite scales from survey items to represent these five factors in EHR adoption decisions and then estimating a series of logistic regression models to test the significance of each factor in predicting adoption status.

Answering this question is important for several reasons. From a theory perspective, this research provides a useful contemporary case for examining the relevance of several issues in the broader literature on diffusion. For example, despite the rapid and wide flow of information in the internet era, this study finds that physician concern about insufficient information is still an important factor in adoption decisions. Also, in contrast to what the literature on diffusion of network technologies would predict, a majority of physicians have now adopted EHRs despite a lack of meaningful interoperability or market convergence on a dominant design.

This research also has important policy implications. First, given that $10.7 billion of HITECH incentive payments have already been made to physicians and other health care professionals through calendar year 2014 (Centers for Medicare and Medicaid Services 2015a), there is value in attempting to measure whether the incentives program is, in fact, influencing physicians' decisions on whether to adopt an EHR. Second, an improved understanding of factors affecting physicians' EHR adoption decisions, especially among recent adopters, can contribute to efforts to evaluate and possibly refine ongoing federal policies to promote EHR adoption. For example, the finding above that a majority of physicians have now adopted EHRs despite a lack of meaningful interoperability or a dominant design indicates that more aggressive federal policies are needed to push progress towards interoperability, given that many of the intended benefits of EHR adoption for the U.S. health system as a whole require interoperability. Third, beyond implications specific to health IT, an improved understanding of the underlying factors that are influential to physician decisions on adoption of a complex innovation is important at a time when system-wide reform under the Affordable Care Act (ACA) depends on diffusion of many ambitious innovations in health care delivery and financing among physicians, who influence so much of the ultimate, down-stream costs and outcomes for health care utilization. For example, as discussed in Chapter 6, the federal Center for Medicare and Medicaid Innovation (CMMI) is currently working to promote diffusion of practice transformation models among primary care physicians (e.g., the Patient-Centered Medical Home model), and this dissertation's findings suggest that both information support and explicit financial incentives for adoption should be important components of these efforts.

In addition to these broader implications, this research also contributes to the health IT literature with two specific methodological points. First, as discussed above, this study differs from most prior research by focusing on physicians in smaller, physician-owned practices. Second, prior research has tended to define adopters versus non-adopters solely as a binary distinction based on whether or not the physician is using an EHR at a given point in time. The research herein uses this definition of adoption for specifying an initial set of models, but, as described in Chapter 3, two other definitions of the dependent variable provide temporal alternatives in defining adoption status. One alternative definition uses a multinomial logistic regression specification to reflect three possible adoption statuses in cross-sectional data: using an EHR, in the process of adoption, or not yet in the process of adoption. A second alternative specification uses a longitudinal approach by starting with physicians who were not yet using an EHR in 2011 and then divides that group into those who remained non-users in 2012 and those who became an EHR user in 2012. Thus, this multi-faceted approach to the temporal aspect of adoption status also sets this research apart.

1.4 Overview of data and methods

This dissertation addresses the research question above with a series of logistic regression models that analyze a national survey of office-based physicians – the Physician Workflow Supplement to the National Ambulatory Medical Care Survey (NAMCS). Both adopters and non-adopters are sampled in this survey data, and the survey includes a series of questions asking physicians about the importance of different potential adoption facilitators or barriers. The methodology for this research includes creating a set of composite scales from groups of these survey items. Each statistical model offers an alternative specification for testing which of the explanatory variables are significant predictors of EHR adoption status among physicians and the comparative magnitude of those relationships.

1.5 Structure of the dissertation

Chapter 2 of this dissertation reviews the literature on diffusion of innovation and its specific application to the case of EHR adoption. Chapter 3 describes the data and methods used in this research, including a factor analysis that supports the set of composite scales representing the underlying adoption factors examined in this study, the rationale for the various logistic regression model specifications, and other key methodological decisions such as the focus on physicians working in smaller, physician-owned practices. Chapter 4 provides useful context for the analysis by describing key developments in federal policy to promote diffusion of health IT, including implementation to date for relevant provisions of the HITECH Act. Chapter 5 presents and interprets the results of the multiple statistical models, and because one finding underscores the influence of the HITECH financial incentives, this chapter also includes a deeper discussion of physician participation in the incentives program. Chapter 6 presents conclusions, limitations of the analysis, and implications for policy and future research.

Chapter 2. Theories Of Diffusion And Applications To Health IT

Early literature on how an innovation diffuses among potential adopters tended to cluster around two competing models. Sociologists traditionally explained diffusion as driven by the spread of information about an innovation, such that those with better information adopt sooner than those who lack sufficient information. In contrast, classical economic theory argued that potential adopters have sufficient information but differ in the costs and benefits they would realize from adoption of the innovation – the net profitability of adoption. Subsequent research has given weight to both information and profitability, particularly for innovations like information technology that have network effects – meaning an innovation that becomes more valuable to adopters as the aggregate level of adoption increases. Consistent with these theories, government policy instruments to promote diffusion of beneficial technologies have often focused on providing information, subsidies, or both. This chapter begins with a review of several general theories of diffusion and associated policy options and then discusses their specific application to health IT.

2.1 Information and social contagion

The early studies of diffusion as a discipline were promoted by sociologists who emphasized differences among potential adopters in the level of information they possessed about an innovation. Ryan and Gross (1943) published a study of hybrid corn adoption in two Iowa farming communities, which found that 46% of farmers (a plurality) cited neighbors as the most influential factor influencing their adoption of hybrid corn, with an even higher percentage among the later adopters. Marketing sources, especially salesmen, were most important for initial awareness of the innovation, but peers were most important for persuading farmers actually to adopt the new corn. The authors also found the now famous S-curve for the cumulative adoption trend (1943, 21). This research launched the initial academic literature on diffusion of innovation and established the sociological model as driven by communication of information within social systems.

A study of the diffusion of tetracycline among physicians in four cities in Illinois in the 1950's represented a second landmark study in the sociology tradition (Coleman, Katz, and Menzel 1966). Coleman et al. explicitly conducted a social network analysis in which they mapped and analyzed physicians' personal interactions with other physicians, both locally and via travel to conferences, as well as other possible sources of information relevant to drug prescribing (drug salesmen, medical journals, etc.). They also analyzed relationships between physician characteristics and adoption of the new drug. Consistent with the Ryan and Gross findings, Coleman et al. found two distinct mechanisms for how the flow of information leads to adoption: 1) basic awareness of the innovation, for which commercial sources such as marketing efforts are often most important, and 2) what the authors termed "legitimation," which is a process of persuasion in which potential adopters actively communicate with or tacitly observe peers, especially opinion leaders, who have already adopted (Coleman, Katz, and Menzel

1966, 64; Rogers 2003, 67). Awareness is necessary for adoption but rarely sufficient, as potential adopters must still evaluate the innovation before they are persuaded to adopt (Coleman, Katz, and Menzel 1966, 55). Rogers (2003, 175) describes persuasion as a key stage in the adoption process – the point at which a potential adopter obtains information about the innovation and decides the credibility and significance of all the information received. When potential adopters lack sufficient information for evaluation, they may delay their decision. Some might actively search for better information, while others might wait more passively. In some cases, however, the evaluation and persuasion process can be truncated if legitimation verges into active or tacit pressure to adopt, rather than simply a more benign flow of positive information about the innovation.

Another important finding by Coleman et al. is that doctors who were more socially integrated with their peers adopted more quickly than doctors who were more socially isolated, and Coleman et al. likened the diffusion process to the dynamic of an epidemic, in which diffusion accelerates based on the degree of interpersonal contacts (1966, 111). This epidemic model has also been referred to as "social contagion" (Burt 1987; Angst et al. 2010).

In a broader review of the sociological literature, Rogers (2003) echoes these findings that earlier adopters tend to be more socially integrated in networks involving interpersonal communication and also more active in seeking information about an innovation. We will return to this linkage between early adopters and the importance of information in Chapter 3, when developing hypotheses that might explain the factors significant to physician adoption of EHRs.

Also, while awareness and legitimation are two commonly cited mechanisms for how information drives diffusion, when an innovation is more complicated a third type of information flow that can also be important is expertise – i.e., knowledge of how to implement and use the innovation. Expertise can also support legitimation, as peers who are seen as having expertise concerning the innovation can be especially persuasive. More complex innovations are likely to require a sufficient flow of expertise to give potential adopters confidence that they can actually implement the adoption successfully.

2.2 The profitability of adoption

Griliches (1957) launched economists' first major entry into the diffusion field with a re-analysis of the hybrid corn case that had generated such interest among sociologists. Griliches analyzed the rate of hybrid corn adoption by farmers within geographic areas and seed manufacturers' development of hybrid corn varieties for specific areas. He found that farmers adopted hybrid corn more quickly in geographic areas where it was more profitable, and he found that manufacturers prioritized development of area-specific seeds for those areas where the expected returns on the research investment would be highest. Thus, Griliches is credited with the theory that differences in the rate of adoption of an innovation are due primarily to heterogeneity in the profitability of adoption among potential adopters.

Mansfield (1961; 1963) then provided broader support for Griliches' basic finding on profitability with research on diffusion of a range of technologies in different industries. In addition to confirming that diffusion depends on the profitability of adoption, Mansfield also found that as the cost of adoption increases, larger firms are likely to adopt earlier than smaller firms, given larger firms' greater ability to absorb financial risk and their easier access to investment capital. In addition, though, Mansfield found that firms become more likely to adopt as the percent of existing adopters increases -- "as information and experience accumulate, it becomes less risky" to adopt (1961, 746). Not only is this finding on the importance of legitimation consistent with the sociologists' epidemic model, but Mansfield (1961, 746) specifically acknowledges Coleman et al. in discussing similar prior findings. While Coleman's legitimation process typically involves opinion leaders or peers explicitly conveying positive information which reduces recipients' uncertainty about an innovation, Mansfield also suggests that legitimation can sometimes have a more coercive element, as competitive pressure can motivate adoption among firms even when they themselves remain uncertain about the costs or benefits of adoption, if they observe widespread adoption by competitors (1961, 746).

Rosenberg (1972) further refined the cost:benefit explanation for gradual diffusion over time by arguing that a new technology typically improves over time, often along with a decrease in cost, and this maturation improves the technology's cost:benefit ratio enough to attract adopters who had previously declined. Rosenberg describes innovation as "a gradual process of accretion, a cumulation [sic] of minor improvements, modifications, and economies, a sequence of events where, in general, continuities are much more important than discontinuities" (1972, 7). He argues that "it is the speed with which performance characteristics are improved, techniques modified to meet the needs of specialized users, and the price of the invention gradually reduced, which determines its acceptability among an increasingly wide circle of potential users" (1972, 20). While not true for every innovation, Rosenberg's point seems particularly relevant to diffusion of more complex, costly technologies such as information technology.

2.3 Network effects and the need for standards

Under both the information and profitability models, the question of adoption can evolve from a simple, binary yes/no decision to an additional choice of "not yet." The information model supports delay as the wait for information to reduce uncertainty, while under the profitability model "not yet" can reflect a rational expectation of a future improvement in the benefit:cost ratio for adoption. Typically the cost of adoption is largely incurred up front as sunk costs while the benefits may accrue gradually. When coupled with uncertainty about the precise timing and level of benefits to be realized, this timing issue creates what economists have termed an "option value" for delaying adoption (Hall 2005, 466; Stoneman 2002, 8).

Differences in information and the cost-benefit ratio of adoption, across potential adopters and across time, are all relevant in the special case of network technologies, which include information and communication technology such as EHRs. One key characteristic of network technologies is that they offer increasing returns, which means the technology's value to a given adopter increases as the overall number of adopters increases (Hall 2005; Stoneman 2002, 72). The increasing value as adoption increases can be due to rising marginal benefits (telephones and fax machines are often cited as intuitive examples), falling marginal costs (for technical support, skilled labor, complementary products, etc.), or both. Network technologies also typically require interoperability, which in turn requires standards and often a dominant design (Hall 2005). Even if a potential adopter believes there are net benefits to a new technology, with a network technology would-be adopters may be concerned with selecting a version that will become obsolete if it does not meet standards necessary for interoperability. This concern is reinforced when there are large sunk costs for adoption and high costs for switching to a different version after an initial adoption.

Faced with uncertainty over which version of the technology to adopt in the absence of interoperability, potential adopters may delay their adoption until they are confident a sufficient standard exists for interoperability – a version of the "not yet" discussed above. Such a standard often results on a de facto basis from emergence of a dominant design, at which point adoption can increase rapidly (Geroski 2000; Stoneman 2002, 8).

The literature on network effects also demonstrates that the strong original differences between the information and profitability explanations of diffusion have, in many cases, evolved to recognize significant overlap between these models. For example, while the diffusion dynamics for network technologies have often been addressed primarily from an incentives perspective, the flow of information about adoption is an essential element of the band-wagon effect that leads to a dominant design. Hall (2005, 462) acknowledges that a focus on cost:benefit calculations "ignores the social feedback effects ... that might result from one individual adopting and therefore encouraging another." This encouragement need not even be a proactive communication process; the encouragement can occur tacitly as a potential adopter observes that peers (perhaps competitors) have adopted – one of Mansfield's findings discussed above. More generally, Stoneman and Diederen (1994, 920) observe that "the efficiency of a market for a new technology is, more than other markets, constrained by both information asymmetries and deficiencies."

Meanwhile, although not directly tied to the network technology model, a leading proponent of the information model acknowledges that "relative advantage," which economists would view as the benefit:cost ratio or profitability of adoption, is one of the strongest predictors of diffusion (Rogers 2003, 233). Because potential adopters typically have imperfect information about costs and benefits, however, a concern with profitability often still involves a real-world flow of information among adopters and potential adopters. Rogers (2003, 233) credits peers conveying their individual experiences of relative advantage as counting much more than scientific assessments based on data or other third-party analysis. Thus, Rogers (2003, 14) ties relative advantage back to an information problem by characterizing diffusion as "essentially an information-seeking and information-processing activity in which an individual is motivated to reduce uncertainty about the advantages and disadvantages of the innovation." Nonetheless, in many cases there is a blurring of the lines on the roles of information versus profitability in the diffusion process.

Returning to the case of a beneficial technology with network characteristics, an important ongoing question is how best to promote interoperability: should market forces be allowed to play out or should the government intervene in recognition of a positive externality (a type of market failure)? This question is important not only for achieving the intended benefits of a network technology, but also to promote adoption itself given the expectation described above that potential adopters would delay adoption until interoperability is achieved. In the absence of government intervention, Katz and Shapiro (1986) describe two general paths to interoperability. First, firms can cooperate in designing and modifying their products to be compatible, but only if enough firms, including those with significant market share, have sufficient incentive to cooperate voluntarily. Market leaders may believe their interests are better served by locking in their installed customer base due to high switching costs in the absence of interoperability, especially since a large existing market share can also make a vendor more attractive to future adopters. As an alternative to cooperation, standardization can occur in the market because enough consumers select the same product design such that other vendors are forced to adapt to that dominant design to stay viable.

Research on emergence of standards and a dominant design under market forces has led to a broader, more complex model that characterizes diffusion as an evolutionary process. In addition to drawing on concepts from the scientific theory of evolution, this model again incorporates aspects of both the information and profitability models of diffusion. Anderson and Tushman (1990, 606) describe the evolutionary process of diffusion as beginning with a "technological discontinuity," which is followed by an "era of ferment" initially characterized by intense competition between the old and new technological regimes or paradigms. This ferment era is also characterized by intense competition among varying product designs for the new technology, as experimentation is fed by the multiple channels and directions of feedback described above (between and among customers and suppliers). This intra-class variation and uncertainty in the ferment era then ends when a dominant design emerges. At that point, remaining technological progress occurs as a series of incremental refinements, driven again by feedback to suppliers as the growing base of adopters begins to gain proficiency with the new technology. While the evolutionary model blends aspects of all three prior models discussed above (information, profitability, and network effects), the evolutionary model also extends the importance of information by acknowledging a greater role for active and tacit communication in multiple directions, not only between adopters and potential adopters but also between adopters and suppliers. In addition to introducing the role of suppliers in diffusion, the more complex environment in the evolutionary model allows recognition of other actors as well, including regulatory agencies, industry associations, and committees that facilitate communication of expertise and interests among multiple stakeholders (P. Anderson and Tushman 1990, 628).

2.4 Government policy options to promote diffusion

Consistent with the research history above, three common policy options when government wishes to intervene to promote diffusion are: 1) provision of information, 2) promotion of standards if a network technology lacks interoperability, and 3) provision of subsidies. Under the first approach, the type of information provided can vary depending on the specific need. For example, if the potential pool of adopters lacks awareness of the innovation or lacks sufficient information about its benefits, government-sponsored marketing campaigns can fill those respective knowledge gaps. For a complex innovation, if the potential pool of adopters lacks sufficient expertise for implementation, government can sponsor technical support. A classic example of this technical support option is the agricultural extension program which provided expertise to local American farmers adopting agricultural innovations during much of the 20th century (Rogers 2003, 165). As will be seen in Chapter 4, the HITECH Act includes a similar model with its Regional Extension Center program.

On the other hand, if lack of standards for interoperability creates a market failure, as discussed above for network technologies, then government can intervene to promote standards through multiple policy instruments, including regulation and procurement. One regulatory option is to aggressively mandate specific design standards that commercial products must meet, while a less aggressive approach would have the government mandate certain capabilities, while allowing different designs that can achieve those capabilities. The latter case may require greater cooperation among competing suppliers to ensure that their different designs can still achieve the mandated capabilities, such as electronic exchange of data among IT products. A rationale for this less aggressive mode of intervention is that the government is likely to lack the information to determine which standard is the best (Katz and Shapiro 1994, 113). David (1987, 210) refers to the paradox of the "blind giants;" government agencies have the most power to set standards early in the diffusion process, before a particular design gains too large a market share, but this early phase is precisely when regulators lack sufficient information to choose the optimal standard. Some theorists argue that under certain conditions market forces are also capable of locking in an inferior design for a technology with network effects, as random events can lead to enough early market share for an inferior design that a tipping point is reached and herd behavior then propels that inferior design to a dominant market share (Arthur 1989). David's (1985) history of the QWERTY keyboard serves as a prominent narrative of lock-in by market forces, although proponents of the market lock-in theory also cite more recent examples such as Microsoft's DOS software (Arthur 1996). Yet other scholars are skeptical that market forces have actually locked in inferior designs and vigorously challenge the details and conclusions in specific cases, including the QWERTY and MS DOS examples (Liebowitz and Margolis 1990; Liebowitz and Margolis 1998; Kay 2013; Margolis 2013).

In some cases government can drive a standard via a centralized procurement process. At the most extreme, there are some technologies that a government may simply decide to procure and distribute on its own in lieu of a more traditional diffusion process. For example, governments sometimes centrally procure vaccines for direct distribution to medical providers. A more indirect scenario involves the government specifying its own requirements for a technology in a procurement that is large enough and timely enough to cause vendors to adopt those requirements as a de facto standard for other customers as well – i.e., the government procurement requirement effectively becomes the dominant design.

The third common policy intervention, provision of subsidies to adopters, can accelerate diffusion by improving the benefit-cost ratio for adoption. A subsidy will generally increase adoption as long as supply is competitive, so that suppliers cannot absorb the value of the subsidy with price increases (Stoneman and Diederen 1994, 925). However, the magnitude of a subsidy's impact on the rate of adoption is uncertain and depends on many factors, including the size of the subsidy relative to the cost of adoption, the timing of the subsidies, and the relative importance of other possible barriers to adoption. Stoneman and Diederen (1994, 925) note that the availability of a subsidy must be temporary, so that potential adopters will accelerate their adoption in order to take advantage of the subsidy. The efficiency of subsidies will also depend in part on what share of recipients would have adopted anyway, and how much those recipients actually accelerate their adoption in response to the subsidy. In some subsidy programs, even those who adopted before the start of the program may be eligible, although the efficiency loss for paying existing adopters may be mitigated if the subsidies are tied to the intensity of use of the new technology rather than simply its acquisition. This type of approach focused on intensity of use rather than acquisition is a key element of the current federal subsidies for adoption of electronic health records, as will be seen in Chapter 4. Finally, it is worth noting that in addition to creating a positive financial incentive for adoption through a subsidy, government can also incentivize adoption by creating a financial penalty for non-adoption. As described further in Chapter 4, the federal EHR incentives program employs a carrot-and-stick combination of both subsidies and penalties.

2.5 Barriers to adoption of EHRs

The theories above from the general literature on diffusion are evident in several specific barriers to adoption that have frequently been cited in the health IT literature. Two commonly cited barriers to EHR adoption in the U.S. fit well within the profitability model of diffusion: 1) the high financial cost of EHR adoption, and 2) a misalignment of financial incentives in which those bearing the cost of EHR adoption are unable to capture the theorized benefits. EHRs also fall under the network technology model, and lack of standards for interoperability has also been advanced as an explanation for slow diffusion relative to computerization in other sectors of the economy. The technological complexity of EHRs has also been frequently mentioned in the literature, with implications both for product selection (in tandem with the lack of standards for interoperability) and for implementation and usability. Each of these issues is reviewed below.

2.5.1 Financial barriers to EHR adoption

As described below, EHR adoption is an expensive undertaking entailing significant direct and indirect costs. Direct costs include the up-front acquisition cost of the system and related hardware requirements as well as ongoing annual costs for licenses, upgrades, and IT support staff. Indirect costs include lost productivity during an initial implementation period, if not longer. Fleming et al. (2011) carefully analyzed gross EHR implementation costs for a large network of primary care practices in Texas (the HealthTexas provider network, with 26 practices with over 450 primary care physicians). Fleming et al. found combined direct and indirect costs that averaged $32,409 per physician through the first two months of implementation and another $14,250 per physician for maintenance through the first year after implementation. As a large network which staggered implementation across its many sites, HealthTexas benefitted from lessons learned at early sites and amortization of the organization’s overall fixed costs across many sites – two advantages that would not apply in the case of small, independent physician practices.

In a study examining 14 small or solo physician practices, Miller et al. (2005) found initial implementation costs of $43,826 per health care provider and ongoing annual costs per provider of $8,412. In this study, however, “provider” included not only physicians but also nurse practitioners and physician assistants. Based on data in the study indicating that physicians accounted for approximately 75% of the billing providers, adjusting the results to a per-physician basis would appear to increase the average adoption costs by approximately one-third, to approximately $58,000 for initial implementation and approximately $11,000 in annual ongoing costs. There was also great heterogeneity in adoption costs among the 14 practices (Miller et al. 2005, 1130).

Given these initial adoption costs of $30,000 to $50,000 per physician and ongoing annual costs of $10,000 to $15,000 per physician, the cost of EHR adoption may be a significant barrier in its own right, and this is a useful hypothesis to test in this present research, as will be discussed in Chapter 3. However, a high cost is not automatically a barrier to adopting a new medical technology, as health care providers often undertake large financial investments when they expect a positive return on investment (ROI), such as purchase of expensive imaging equipment or expansion of physical capacity (e.g., an ambulatory surgery facility or a hospital wing). These investments typically generate additional service delivery, and in the health system’s traditional fee-for-service payment environment, an increased volume or intensity of services translates into increased revenue. What makes health IT different is that the business case to support a large investment in EHR adoption is greatly weakened by misaligned financial incentives concerning who incurs the costs versus the benefits of EHR adoption (a positive externality, which is a type of market failure). These incentives related to EHR adoption are misaligned for health care providers, patients, and insurers.

If an EHR helps a physician to avoid ordering unnecessary or duplicate diagnostic services such as lab tests or imaging, or if the EHR prompts a physician to prescribe a less expensive generic drug, the health insurance plan rather than the physician is likely to realize the bulk of such savings (except in the important case of an integrated delivery system, as discussed below). In fact, if the avoided services would have been provided by the physician with the EHR (e.g., from in-house laboratory or imaging capacity, or from an additional visit to discuss the results of an ordered test or scan), then in the traditional fee-for-service environment the care avoided would actually represent a loss of revenue to the physician practice. In the traditional fee-for-service provider payment environment, physicians have been paid for the work they do, not the work they avoid through an EHR. Physicians have also found it difficult to charge insurers for savings from EHR adoption because, as discussed below, to date it has been difficult to measure or prove actual savings from EHR adoption. Heterogeneity of patient casemix has also meant insurers have typically lacked reliable information to identify higher quality, more efficient physicians.

Another misalignment of financial incentives is that patients traditionally have faced a low share of the cost of care and often are not even aware of the ultimate cost of their care, especially at the point of service, such that it is very difficult for physicians to compete for patients on the basis of price. The one time patients typically are aware of the price they face for physician services is when they face a fixed copayment, but copayments normally would not vary by individual physician and therefore also would not affect a patient's choice of physician. Thus, delivering more efficient care with an EHR is unlikely to offer a significant price advantage that could attract more patients.

Given that health insurers have been identified as the likely recipient of the bulk of EHR-generated savings on health care costs, one might initially expect that health insurance companies should be willing to reimburse physicians for the cost of EHR adoption. However, commercial insurers also have poor incentives to pay for EHR adoption. First, there has been little convincing evidence to date of actual health care cost savings connected to EHR usage, and commercial insurers are reluctant to pay for theorized savings. A widely cited review of the literature through early 2004 by Chaudhry et al. (2006, E–19) concluded, "With respect to the business case for health information technology, we found little information that could empower stakeholders to judge for themselves the financial effects of adoption." A follow-up review of subsequent literature from 2004 to 2007 by Goldzweig et al. (2009) continued to find limited empirical evidence for HIT benefits. Buntin and other analysts affiliated with ONC focused on the literature from 2007 to early 2010 and found it "reassuring" in terms of positive effects from health IT, but few of the studies in this review explicitly examined cost impacts (Buntin et al. 2011, 470). Finally, a 2010 study by DesRoches et al. (2010, 645) found a "striking lack of relationship" between EHR adoption and the quality or efficiency of hospital care, across a range of metrics. The authors characterized this finding as "sobering," although they noted that most of the adopter hospitals in the data were recent adopters (DesRoches et al. 2010, 644).

From the perspective of health insurance plans, this uncertainty regarding health care cost savings from EHR adoption is also driven by the risk of unintended impacts on physicians' billing practices in the fee-for-service payment environment. As far back as 2005, the first National Coordinator for Health IT, David Brailer, voiced a concern that physicians would attempt to recoup their EHR investment through improved charge capture, meaning that EHRs may lead physicians to increase their coding of patient severity in the claims they submit for payment by insurers (Cunningham 2005). This effect can occur through several mechanisms – some of which may be interpreted more benignly than others. For example, to the extent a physician previously was less attentive about manually documenting on a paper chart all the services actually provided to a patient, the EHR will often capture that detail automatically for inclusion in billing. EHR checklists and cut-and-paste features for documenting the complexity of a patient visit also may make it easier for physicians to intentionally or mistakenly document more complex patient encounters – known as upcoding. Further, many EHRs will often prompt the physician to consider providing additional services which may be appropriate for a patient, such as taking a medical history if one is not already present in the record or providing preventive care services for which a patient may be eligible (e.g., an immunization, a cholesterol screening, smoking cessation counseling, etc.). While such additional services would be genuine and may have some long-term benefit at the societal level, in the near term they would increase provider revenue and system-wide health care costs.

Adler-Milstein, Green, and Bates (2013) found empirical support for concern about charge capture in a financial analysis of 49 physician practices who participated in an EHR adoption project in Massachusetts. A key discriminator between those practices who achieved a positive ROI and those who failed to do so is whether they were able to increase their revenue, rather than how much they reduced costs. While a small portion of the increased revenue was due to a higher volume of visits for some practices, in the bulk of the cases it was higher revenue per visit, due particularly to how coding of visits changed with the EHR. More prominently, in 2012 the *New York Times* reported on concerns that inappropriate use of certain EHR documentation features may be partly responsible for an increase in the average coded severity of Medicare claims submitted by both hospitals and physicians (Abelson, Creswell, and Palmer 2012). Within days of this report, the Obama administration announced a program of increased reviews of Medicare claims coding and also warned national hospital and physician associations that health care fraud would be aggressively prosecuted (Abelson and Creswell 2012).

In addition to the lack of concrete evidence of health care cost savings associated with EHR adoption, a second disincentive for commercial health insurers is a free-rider problem because physicians and hospitals usually contract to be in multiple insurers' networks, so the first-mover insurer who subsidized EHR adoption by physicians and hospitals would bear that cost while competing insurers would reap the same benefits if the EHR adopters begin delivering more efficient or higher quality care. A third disincentive for commercial insurers to pay for EHR adoption is that because enrollment in commercial insurance is typically tied to employment, as workers move from one job to the next there is turnover among an insurer's covered population. This turnover in a given commercial insurer's population means that any theorized longer-term benefits of health IT in terms of patients' improved health outcomes may largely accrue to a different insurer.

This tension between turnover in a commercial insurer's population and longer-term benefits from EHR adoption is an important rationale for the HITECH Act's reliance on the federal Medicare program (and, to a lesser extent, Medicaid) as the source of subsidies for EHR adoption. Unlike commercial insurers, Medicare covers the vast bulk of Americans aged 65 and over, as well as many disabled beneficiaries under age 65, and therefore Medicare does not compete with other insurers for market share. Also, once beneficiaries enroll in Medicare, they typically remain a Medicare beneficiary until death, so the population turnover that weakens the business case for commercial insurers to subsidize EHR adoption is not a problem for Medicare. Finally, to the extent EHR diffusion actually helps to maintain the health of Americans before they reach normal Medicare eligibility at age 65, Medicare would benefit financially by inheriting a healthier mix of beneficiaries.

In addition to Medicare, another important exception to the generally poor incentives for health plans to fund EHR adoption occurs when the EHR adopter is part of an integrated delivery system which has dual responsibility as both a health plan and a provider of care. It is not a coincidence, and has been widely observed in the literature, that two of the early, prominent adopters of health IT are the Kaiser Permanente health maintenance organization (HMO) and the Veterans Health Administration (VHA) (Congressional Budget Office 2008; Kleinke 2005; Chen et al. 2009; A. Jha et al. 2003; Asch et al. 2004). While an analogy to mass production by large manufacturing corporations only goes so far given the complexity and service-oriented nature of health care delivery, Kaiser and VHA are certainly large enterprises that benefit from vertical integration, particularly in their use of information technology. They each operate under a health care budget to deliver care to an enrolled population, using their own physicians, hospitals, laboratories, pharmacies, etc., so IT-driven savings remain within the larger organization that bears the cost of the IT investments. However, the VHA and Kaiser are not especially representative cases for the U.S. health system as a whole, both because of their incentive structure as integrated delivery systems and because they are large enough to fund in-depth customization of an EHR system to fit their own needs rather than simply implementing an off-the-shelf commercial product.

2.5.2 Network effects for EHRs

In addition to the misalignment of financial incentives, a second broad theory advanced in the literature to explain slow adoption of EHRs involves the set of issues attributable to network technologies. As discussed earlier in this chapter, network technologies such as IT introduce diffusion issues including the importance of interoperability standards, the emergence of a dominant design, and the risk of an early adopter getting locked into an inferior or obsolete design. In the context of EHRs, a key type of interoperability would be a routine capability for different EHR systems to electronically exchange and integrate patients' clinical data. Christensen and Remler (2009) emphasize that imperfect information fuels physician and hospital concerns with the risk of selecting an inferior EHR design which proves to be obsolete once standards for interoperability eventually emerge. This concern with product obsolescence is reinforced by high switching costs with EHRs, given the need to input existing patient data, train staff, customize software modules for specific practice needs, etc. Therefore, Christensen and Remler argue that until a dominant design emerges, potential adopters may perceive large risks in the need to select a specific EHR vendor or system, and that this perception can incentivize a delay in adoption even if a physician practice or hospital favors adoption in principle. Compared to IT adoption in other industries, "the value of waiting" is particularly high for health care providers because the penalties for reliance on a poor EHR system can include treatment errors with consequences for patient safety (Christensen and Remler 2009, 1024).

The high switching costs associated with a new EHR system also mean that many small physician practices and smaller hospitals in the U.S. may only have one bite at the apple for EHR adoption, at least for the foreseeable future. A physician or hospital may be left with a system that fails to keep pace with the eventual interoperability requirements that will be essential to realizing the full benefits of an EHR, or a poor design may technically meet interoperability standards but still proves too complicated or cumbersome to serve as a foundation for transforming care delivery within the organization. Notably, in focus groups of physicians convened for a 2006 Robert Wood Johnson Foundation (RWJF) report on health IT (several years before the HITECH Act), poor usability and fear of obsolescence ranked only after financial barriers as concerns about EHR adoption (Blumenthal et al. 2006, 46). This fear of obsolescence suggests that challenges in selecting a specific EHR vendor and product could be a significant barrier to adoption – another hypothesis to be addressed in Chapter 3's discussion of methodology for the present research.

2.5.3 The complexity of EHR technology

Meanwhile, physician concern with the usability of EHRs, as noted in the RWJF study above, fits well with Rogers' identification of complexity as one of the key attributes of a technology that influence its diffusion. Rogers (2003, 16) defines complexity as the extent to which the innovation is perceived as difficult to use and understand. The health IT literature emphasizes that EHR systems are complex to implement and to use effectively (O'Malley et al. 2009; Mandl and Kohane 2012; Kellermann and Jones 2013). Before even getting to the higher level questions of whether EHRs will reduce health care costs or improve underlying quality of care, accounts of physician adopters mention more mundane problems with system usability and reliability (Blavin et al. 2013; Friedberg et al. 2013; Fernandopulle and Patel 2010; Skolnik 2011). Blavin et al. (2013, 4) found that "a major consensus in the literature is that, in general, EHRs are often poorly designed for clinical purposes and need to be continuously customized to meet the needs of the organization." Friedberg et al. (2013, 33) found physician complaints about their EHRs included usability, the time required for data entry, interference with patient interactions, "inefficient and less-fulfilling work content," lack of interoperability, and "degradation of clinical documentation." Friedberg et al. (44)

did also find, however, that 61% of physicians surveyed believed their EHR improved quality of care and only 18% preferred paper records to their EHR. Thus, concerns about operationally implementing and using an EHR may be another significant barrier to adoption for many physicians.

2.6 Summary

To recap, this chapter has identified several theories which may have relevance in predicting physician decisions on adoption of EHRs, including the importance of information, the profitability of adoption, the importance of interoperability for a network technology, and challenges in actually implementing and using this complex technology. Chapter 3 will present a methodology and hypotheses for testing the extent to which physicians' concerns about each of these issues predict EHR adoption status for small, physician-owned practices. For example, while the cost associated with an EHR is widely cited as a barrier to adoption, to what extent are physicians' concerns about the cost of EHR adoption actually a predictor of their adoption status? Similarly, to what extent is EHR adoption status predicted by physicians' views on the importance of improved information as a factor in their EHR adoption decision? The analytical approach for this study is not driven by an a priori expectation of which factors, among the multiple issues discussed in this chapter, are, in fact, significant predictors of adoption status. Rather, the methodology described in Chapter 3 presents a balanced effort to test and compare the significance of each of the potential adoption factors identified for this analysis, with the understanding that more than one factor or theory may be relevant for understanding physician decisions on whether to adopt the complex innovation that an EHR represents.

Chapter 3. Data And Methods

The key data source for this dissertation is a recent U.S. government survey of non-federal, office-based physicians in 2011 and 2012 – the Physician Workflow Supplement to the National Ambulatory Medical Care Survey (NAMCS). The Physician Workflow Supplement was funded by the Office of the National Coordinator for Health Information Technology (ONCHIT) but was administered by the agency that is responsible for the basic NAMCS survey – the National Center for Health Statistics (NCHS) within the Centers for Disease Control (CDC). The basic NAMCS survey of physicians has been fielded for several decades and, as the source for hundreds of published health policy studies (National Center for Health Statistics 2013), NAMCS has been well vetted by health policy researchers. In contrast, the first year of data for the Physician Workflow Supplement (2011 data) only became available in 2012, and due to NCHS privacy policies, researchers external to NCHS can only access the Physician Workflow data on a restricted, on-site basis. For this dissertation, the author received on-site access to Physician Workflow data for 2011 and 2012.

The Physician Workflow Supplement reflects a stratified sampling design, with strata defined by state. Survey weights developed by NCHS were applied in all analyses herein to ensure appropriate population estimates. Standard errors were calculated using

Taylor Linearization to account for the complex survey design. All analyses were performed with Stata version 13.

The 2011 survey sampled 5,232 eligible office-based physicians and ultimately obtained 3,180 eligible responses – a 60.8% unweighted response rate among those determined to be eligible for the survey (Jamoom et al. 2012). As a longitudinal survey, both the 2011 and 2012 rounds started with the same sample of physicians, but in 2012 there were 2,567 eligible responses. The lower number of responses reflects a lower unweighted response rate (56.4%) among those physicians estimated to be in-scope in 2012 but also that a portion of the 2011 sample was no longer in-scope in 2012.[3] These 2011 and 2012 response rates for the Physician Workflow Supplement are quite consistent with response rates in the literature involving physician surveys. Cummings, Savitz, and Konrad (2001) reviewed 257 physician mail surveys published from 1986 to 1995 and found a mean response rate of 61% and a median rate of 62%. Mcleod et al. (2013) reviewed 117 surveys of health care providers published from 2000 to 2011 and also found similar response rates.

Both adopters and non-adopters are sampled for the Physician Workflow Supplement. Certain questions are asked of both groups, but other questions are specific to adopters or non-adopters. Further, when the second year of the survey was fielded in 2012, some questions from the 2011 version were dropped and new questions were added. As a result, variables available in the survey data can differ based on adoption

---

[3] For a 2012 response rate, it is appropriate to estimate the number of eligible physicians within the overall sample because an operational change in 2012 limited NCHS's ability to formally determine eligibility status for many non-respondents in the sample.

status and based on the survey year, including some of the items related to adoption facilitators and barriers. However, because 1,966 of the responding physicians responded in both 2011 and 2012, and there is a common respondent identifier code across both years, it is possible to link 2011 and 2012 responses for this sub-group. One of the regression models described below takes advantage of this linkage capability.

3.1 Key sources of error in survey data

In analyzing survey data, it is important to be aware of possible sources of error in the data. Many possible sources of error are discussed in the literature on survey methods – hence the concept of Total Survey Error (TSE), which Paul Biemer (2010, 817) defines as "the accumulation of all errors that may arise in the design, collection, processing, and analysis of survey data." Of all these potential sources of error in survey data, Groves et al. (2009, 59) identify nonresponse bias as the most common concern, especially among end-users of the data. Researchers often have confidence that experienced survey organizations such as NCHS can satisfactorily minimize most other types of errors, but non-response is difficult to control and sometimes difficult to detect. One tool for survey administrators is to invest resources to increase response rates, such as by fielding multiple waves of a mail survey and also by following up to obtain late responses by phone – both of which were done by NCHS for the Physician Workflow Supplement.

Survey administrators also can conduct a nonresponse analysis. While NCHS has not yet published a nonresponse analysis for the NAMCS Physician Workflow Supplement, NCHS did adjust the survey's analysis weights to account for estimated nonresponse error based on the characteristics of late respondents whose data were obtained by telephonic follow-up after they failed to respond to three waves of the mail survey (Jamoom et al. 2012). While imperfect, this technique of using information on late respondents from special follow-up efforts to serve as a proxy for nonrespondents is a common technique for estimating nonresponse adjustments to survey weights (Lineback and Thompson 2010; Halbesleben and Whitman 2013).

Also of interest, NCHS has presented details on an in-depth nonresponse analysis for another EHR-related supplement to NAMCS known as the Electronic Medical Record (EMR) Supplement (Cai and Shimizu 2012). The findings of this analysis have some relevance to the Physician Workflow Supplement because there are many similarities between these two EHR-related supplements to NAMCS, including a high degree of overlap between their samples. This analysis by Cai and Shimizu found that for certain narrow physician characteristics there were differences in response rates that were statistically significant, but based on my own inspection of their detailed results even the statistically significant differences they found do not seem large enough in a practical sense to suggest meaningful nonresponse bias in this other NAMCS EHR survey.[4] This conclusion does not necessarily transfer to the Physician Workflow Supplement, but it is helpful to know that a very similar EHR survey did not appear to incur major differences in response rates across a range of objective physician characteristics. In any case, as noted above, NCHS did make adjustments to the Physician Workflow weights using late

[4] For example, only one physician specialty had a statistically significant difference in response rates, and even this 70% response rate among pediatricians was not dramatically higher than the 64% average rate across all specialties. Similarly, there was a statistically significant difference between the 2.64% of responding physicians who fell into the under-35 age group and the 3.54% of the sampling frame physicians who fell into that age group, yet this small but detectable difference does not appear to indicate a meaningful difference in the age mix of respondents versus the population.

respondents reached by phone follow-up as a proxy for non-respondents. Nonetheless, ultimately researchers and policy-makers must accept the risk of potential nonresponse bias as an assumed caveat to survey-based findings.

While concern about the validity of survey data often focuses on nonresponse bias, Biemer (2010, 823) cautions that too many analysts ignore significant risks of measurement error, which occurs when the response provided does not reflect the true value of that measure for a given respondent. In the context of this dissertation, one risk of measurement error concerns the unit of analysis. There is a distinction in the survey methods literature between surveys targeting individuals or households as respondents, which are often referred to as household surveys, and surveys targeting organizations as respondents, which are generally referred to as establishment surveys. Sudman and Phillips (1994, 1351) note the increased risk of measurement error in establishment surveys because "when reporting about organizational events or issues, informants are typically answering questions about events ... that may be learned second hand." Similarly, Edwards and Cantor (1991, 215) note that "because of differences in size and the nature of interpersonal relationships between households and establishments, respondents to establishment surveys may be less likely to have the kinds of relevant personal memories household survey respondents have." The data available in the Physician Workflow survey reflect the responses of individual physicians, and the survey weights that have already been developed by NCHS also reflect physicians, not practices. Therefore, the formal unit of analysis must remain the individual physician, not the practice. However, one would expect that the EHR adoption decision is typically made by someone or some group on behalf of the physician's practice as a whole. As described below, the key data for this research is a series of questions in the survey asking how much different factors influenced the decision on whether or not to adopt an EHR. Thus there is a risk that some survey respondents may not be knowledgeable of the relative influence of these different factors in the practice's adoption decision. In particular, an individual physician responding to the survey who works in a large practice or a practice owned by a large organization, such as a hospital, health maintenance organization, or university, would seem very unlikely to have direct knowledge of the relative influence of different factors in the EHR adoption decision for the practice.

In part to address this measurement issue, which is critical to this research, the quantitative modeling for this research focuses on physicians who work in physician-owned practices with no more than 10 physicians, while excluding physicians who work in practices larger than 10 physicians or practices owned by larger organizations such as hospitals, HMOs, or universities.[5] A second reason the analysis focuses on physicians in smaller, physician-owned practices is that these physicians are an important target of the HITECH Act, as they typically have fewer resources to support EHR adoption (e.g., in-house IT expertise) and existing literature indicates they have been slower to adopt EHRs (Decker, Jamoom, and Sisk 2012). Physicians working in physician-owned practices of 10 or fewer physicians represent approximately 55% of the unweighted respondents in the 2011 sample, or approximately 58% of the weighted population.

[5] For privacy reasons, the practice size variable in the data available to the author is grouped into size bands based on the number of physicians in the practice, and the largest size band is "greater than 10".

As an additional response to the risk of measurement error due to an unknowledgeable respondent, the analysis also excludes those survey responses where a staff member completed the survey rather than the sampled physician.[6] Examination of the data indicates that most of these responses by an administrative staff member were late responses collected by phone rather than the survey's normal mail mode. Given the telephonic collection mode, it seems unlikely the administrative staff respondent would have had an opportunity to consult with the intended physician, or even any physician, on the relevant questions for the research herein, which ask about the importance of different potential adoption facilitators and barriers. While this would not necessarily be a concern for those questions in the survey that are more objective, for the questions of interest here on issues that influenced the EHR adoption decision there is a high risk that the responses would represent the opinions and perceptions of whichever administrative staff member completed the survey interview. If these staff respondents lacked sufficient knowledge to accurately answer the relevant survey questions about the practice's decision-making on EHR adoption, at a minimum one would expect inclusion of these staff responses to decrease the precision of relevant parameter estimates. Further, if there were a systematic difference in staff views compared to physician views, which would seem quite possible on some of these issues such as concerns over implementation issues, then inclusion of these staff responses would also bias the parameter estimates. Therefore, these staff

[6] In the 2011 data, approximately 30% of the survey responses were coded as completed by office staff rather than a physician. A small number of respondents were also excluded because they gave contradictory responses to different questions related to whether their practice was currently using an EHR.

respondents are excluded from the analysis to ensure that all data reflect the views of physicians rather than their administrative staff.

A second risk of measurement error relevant to this dissertation concerns the challenge of having to rely on survey questions to measure an underlying construct that is not directly observable, such as the influence of information issues on the decision whether to adopt an EHR. Creating a composite scale variable from a set of individual survey items, in order to measure an underlying construct, is a well-established approach to this issue in the literature on survey research methods, for two reasons (DeVellis 2012; Dunteman 1989; Churchill 1979; Sapsford 2011; Spector 1992). First, as Dunteman (1989, 54) argues, “a composite of unreliable measures can be considerably more reliable than any single variable making up the composite.” Sapsford (2011, 222) echoes this point, noting that a composite scale offers a more sophisticated measure for an underlying construct that can provide “a more stable and plausible indicator than any of the individual items.” To the extent measurement error is randomly distributed on both sides of the true population mean, then by averaging item values together in a scale this random measurement error can partially offset across the items comprising the scale. Also, to the extent any given item in the scale may be subject to a systematic bias (e.g., perhaps one question is more prone to misinterpretation or recall bias than the other questions), then by averaging the multiple items the influence of that biased item will be dampened in the composite scale, compared to including the individual items in a model (Churchill 1979, 66). These risks of measurement error are plausible in the present case, and thus the use of composite scales is an appropriate response. Further, individual survey items are likely to represent only a portion of the underlying construct of interest, especially for a broader construct such as "improved information." Churchill (1979, 68) notes: "No single item is likely to provide a perfect representation of the concept, just as no single word can be used to test for differences in subjects' spelling abilities and no single question can measure a person's intelligence. Rather, each item can be expected to have a certain amount of distinctiveness or specificity even though it relates to the concept." Again, this argument supports the use of composite scales in this study.

Some of these benefits of a composite scale could also be obtained by calculating a joint test of significance (an F test) for the same group of survey items that would comprise the composite scale. Such a test would indicate whether there is a detectible relationship between any of the items in the group and the dependent variable, but a single mis-measured item in the group could still have enough influence to sway the result of an F test. More importantly, an F test of joint significance would not indicate the direction of any relationship detected nor the relative magnitude of impact. In contrast, a composite scale can provide both direction and magnitude of impact, although this additional information is useful only if the scale is first judged to be sufficiently valid. Thus, given the prominent role of composite scales in this current research, demonstrating their validity is a necessary and worthwhile investment.

The rationale for which items to include in a scale should be partly informed by existing knowledge of the field, but the methodological literature on scale development also stresses that the item selection for a scale should be supported more empirically as well – for example, with a factor analysis (A. B. Anderson, Basilevsky, and Hum 1983;

DeVellis 2012, 108). Factor analysis is particularly important when a researcher may be measuring multiple latent constructs from a large initial pool of items, as discussed below for this research (Clark and Watson 1995). Rather than relying purely on intuition, a factor analysis provides an empirical basis to support the specific grouping of items into different scales, although a careful factor analysis still requires judgment and a sound theoretical basis (Clark and Watson 1995).

3.2 Development of composite scales for adoption facilitators and barriers

The Physician Workflow Supplement includes a series of 20 questions asking physicians about their experience of different adoption facilitators or barriers. These questions are shown in Table 1 below, along with summary statistics for each question. Each of these questions has three response categories asking the physician whether the particular issue was a major influence/barrier for the EHR adoption decision (reverse scored for this study as a value of 3), a minor one (reverse scored as a value of 2), or not a factor at all (reverse scored as a value of 1).

Table 1. Wording and Statistics for Survey Items Used in Factor Analysis, Weighted for Physician Respondents in Physician-Owned Practices of <= 10 Physicians

Potential Facilitators:
EHR users were asked: How much of an influence did the following have on your decision to adopt an EHR?
Non-users were asked: How much of an influence do you think the following would have on your decision to adopt an EHR?
Response categories (as reverse scored) were: Not an influence=1, Minor influence=2, or Major influence=3

	1 = Not an Influence	2 = Minor Influence	3 = Major Influence	Total	Mean	Obs.
a. Government incentive payments for EHR use	32.6%	35.4%	32.1%	100.0%	2.00	1,052
b. Proposed financial penalties for not using an EHR	27.2%	33.2%	39.6%	100.0%	2.12	1,051
c. Availability of Government-certified products	45.7%	36.2%	18.2%	100.0%	1.73	1,046
d. Assistance with selecting an EHR	43.8%	34.5%	21.7%	100.0%	1.78	1,051
e. Technical assistance with EHR implementation in my practice	26.5%	34.9%	38.8%	100.0%	2.13	1,053
f. EHR systems being used by trusted colleagues	29.5%	35.5%	35.0%	100.0%	2.05	1,050
g. Capability of exchanging information electronically within my referral network	29.4%	38.4%	32.2%	100.0%	2.03	1,056
h. Requirement to use an EHR for maintenance of board certif.	50.0%	20.8%	29.2%	100.0%	1.79	1,042

Potential Barriers:
1. EHR users were asked: Please indicate to what extent you experienced the following as a barrier to implementing an EHR: ...
2. Non-users were asked: Regardless of your plans, to what extent do you view the following as a barrier to adopting an EHR?
Response categories (as reverse scored) were: Not a barrier=1, Minor barrier=2, or Major barrier=3

	1 = Not a Barrier	2 = Minor Barrier	3 = Major Barrier	Total	Mean	Obs.
a. Reaching consensus within your practice to select an EHR	55.5%	32.2%	12.3%	100.0%	1.57	1,046
b. Finding an EHR system that meets your practice's needs	19.3%	34.2%	46.5%	100.0%	2.27	1,049
c. Effort needed to select an EHR system	18.7%	36.1%	45.3%	100.0%	2.27	1,044
d. Cost of purchasing an EHR system	5.4%	17.8%	76.8%	100.0%	2.71	1,050
e. Ability to secure financing for an EHR system	33.4%	37.9%	28.8%	100.0%	1.95	1,037
f. Annual cost of maintaining an EHR system	10.5%	37.5%	52.0%	100.0%	2.41	1,047
g. Loss of productivity during transition to an EHR system	9.6%	30.4%	60.0%	100.0%	2.50	1,051
h. Adequacy of training for you and your staff	13.8%	41.0%	45.2%	100.0%	2.31	1,050
i. Adequacy of EHR technical support	14.4%	45.2%	40.4%	100.0%	2.26	1,049
j. Access to high speed internet	66.8%	26.6%	6.6%	100.0%	1.40	1,047
k. Reliability of the system (e.g., EHR down or unavailable when needed)	20.4%	46.9%	32.7%	100.0%	2.12	1,042
l. Resistance of your practice to change work habits	26.7%	39.9%	33.4%	100.0%	2.07	1,054

To develop composite scales, a principal components factor analysis was performed on this pool of the 20 survey items which ask physicians about their experience of different adoption facilitators and barriers. With only three response levels, the items in this analysis reflect ordinal rather than continuous data, but the use of ordinal or even binary items does not preclude development of a valid composite scale (DeVellis 2012, 190). Clark and Watson (1995, 313) find that even dichotomous response formats typically yield results similar to more traditional Likert-type rating scales with five to seven responses – when "used intelligently, both formats can yield highly reliable and valid scales." Therefore, to account properly for the ordinal nature of the data, polychoric correlations and associated factor loadings were computed using the *polychoric* supplemental package of Stata commands developed by Kolenikov (UCLA Institute for Digital Research and Education 2014; Kolenikov and Angeles 2009; Kolenikov 2014), although similar results were also found with Stata's conventional *factor, pcf* command.

The factor analysis identified five different underlying conceptual categories of potential adoption facilitators or barriers in the survey data:

1. *improved information* (five survey questions address the influence of different improvements in information, such as government certification of EHRs or the opinion of a trusted colleague);
2. *the federal HITECH financial incentives program* (two questions address the influence of government incentive payments and penalties for adoption);
3. *cost barriers* (three questions address the EHR purchase cost, the annual maintenance cost, and financing the cost of adoption);

4. *product selection barriers* (three questions address challenges in choosing an EHR); and
5. *implementation barriers* (six questions address different possible barriers related to operationally implementing and working with an EHR).

Table 2 below shows how the 20 survey items in the factor analysis were grouped into the five composite scales, while Table 3 presents the factor loadings that, along with researcher judgment, supported the highlighted grouping of items in each scale.

Composite scales for each of the five underlying constructs were then calculated as the mean of the items comprising each scale. Because all of the component items have response values of 1, 2, or 3, the resulting scales that reflect the mean of the relevant items can have a minimum value of 1.00 (if none of the items in the scale were reported as having any influence on adoption) and a maximum value of 3.00 (if all of the items in the scale were reported as major influences). Because each scale reflects the mean of multiple items, for many respondents the scale value will fall between integers, allowing for greater differentiation among respondents. For example, with three items comprising the cost barriers scale, if a given respondent rated one item as a major barrier and the other two items as minor barriers, for this respondent the composite value for this scale would be 2.33. Calculating each scale as the mean of those items with high loadings on that factor is a common approach endorsed in the literature which allows more intuitive interpretation of the construct reflected in the scale, is easier to replicate, and typically yields results similar to a complex weighting of items based on their specific factor loadings (A. B. Anderson, Basilevsky, and Hum 1983, 255; Dunteman 1989, 54).

Table 2. Grouping of Survey Items into Composite Scales Based on Factor Analysis

	Improved Information	Cost Barriers	Implem. Barriers	Product Selection Barriers	HITECH Financial Incentives	Not In Any Scale
Potential Facilitators: ***EHR users were asked: How much of an influence did the following have on your decision to adopt an EHR?*** ***Non-users were asked: How much of an influence do you think the following would have on your decision to adopt an EHR?*** ***Response categories (as reverse scored) were: Not an influence=1, Minor influence=2, or Major influence=3***						
a. Government incentive payments for EHR use					X	
b. Proposed financial penalties for not using an EHR					X	
c. Availability of Government-certified products	X					
d. Assistance with selecting an EHR	X					
e. Technical assistance with EHR implementation in my practice	X					
f. EHR systems being used by trusted colleagues	X					
g. Capability of exchanging information electronically within my referral network	X					
h. Requirement to use an EHR for maintenance of board certif.						X
Potential Barriers: ***1. EHR users were asked: Please indicate to what extent you experienced the following as a barrier to implementing an EHR: ...*** ***2. Non-users were asked: Regardless of your plans, to what extent do you view the following as a barrier to adopting an EHR?*** ***Response categories (as reverse scored) were: Not a barrier=1, Minor barrier=2, or Major barrier=3***						
a. Reaching consensus within your practice to select an EHR				X		
b. Finding an EHR system that meets your practice’s needs				X		
c. Effort needed to select an EHR system				X		
d. Cost of purchasing an EHR system		X				
e. Ability to secure financing for an EHR system		X				
f. Annual cost of maintaining an EHR system		X				
g. Loss of productivity during transition to an EHR system			X			
h. Adequacy of training for you and your staff			X			
i. Adequacy of EHR technical support			X			
j. Access to high speed internet			X			
k. Reliability of the system (e.g., EHR down or unavailable when needed)			X			
l. Resistance of your practice to change work habits			X			

Table 3. Factor Loadings, with Grouped Items Highlighted Under Each Factor

	Factor 1: Improved Information	Factor 2: Cost Barriers	Factor 3: Implem. Barriers	Factor 4: Product Selection Barriers	Factor 5: HITECH Financial Incentives
Government incentive payments for EHR use	0.419	0.201	-0.005	-0.034	0.711
Proposed financial penalties for not using an EHR	0.316	0.092	0.076	0.052	0.810
Availability of Government-certified products	0.656	0.158	0.074	0.136	0.451
Assistance with selecting an EHR	0.816	0.130	0.088	0.083	0.203
Technical assistance with EHR implementation in my practice	0.818	0.136	0.084	0.100	0.151
EHR systems being used by trusted colleagues	0.774	-0.036	0.044	0.149	0.074
Capability of exchanging information electronically within my referral network	0.732	0.067	-0.014	0.059	0.136
Requirement to use an EHR for maintenance of board certification*	0.578	0.204	0.004	-0.017	0.404
Reaching consensus within your practice to select an EHR	0.132	0.175	0.074	0.649	0.097
Finding an EHR system that meets your practice's needs	0.242	0.262	0.153	0.720	-0.074
Effort needed to select an EHR system	0.131	0.378	0.208	0.711	0.015
Cost of purchasing an EHR system	0.048	0.843	0.108	0.376	0.124
Ability to secure financing for an EHR system	0.193	0.838	0.197	-0.002	0.085
Annual cost of maintaining an EHR system	0.079	0.837	0.246	0.169	0.092
Loss of productivity during transition to an EHR system	0.033	0.280	0.472	0.438	0.366
Adequacy of training for you and your staff	0.018	0.180	0.696	0.384	0.225
Adequacy of EHR technical support	0.057	0.315	0.698	0.327	0.094
Access to high speed internet	0.025	0.178	0.755	0.219	-0.154
Reliability of the system (e.g., EHR down or unavailable when needed)	0.239	0.297	0.675	0.206	-0.012
Resistance of your practice to change work habits	-0.054	-0.061	0.461	0.399	0.318

* This item is excluded from the Information Scale because conceptually it does not fit well with the other items loading on this factor and this item reflects more of a hypothetical influence, given that EHR adoption typically has not actually been a requirement for maintenance of board certification.

After preliminary decisions on the grouping of items based on factor loadings, theory, and researcher judgment, another important step is to assess a given scale's internal consistency in measuring a single underlying construct. This test is conventionally performed with Cronbach's alpha, a widely used index of reliability for a composite scale of survey or test items (Gadermann, Guhn, and Zumbo 2012, 1; Kent 2001, 209; DeVellis 2012, 108; Sapsford 2011, 237). To account for the ordinal nature of the original survey items, polychoric correlations were again used to calculate ordinal versions of alpha, as recommended in Zumbo, Gadermann, and Zeisser (2007) and in Gadermann, Guhn, and Zumbo (2012). For each of the five explanatory factor scales used in this analysis, Table 4 presents results for the ordinal version of alpha, along with the unweighted mean value and standard deviation for the 1,043 respondents representing the study population of physicians working in physician-owned practices of 10 or fewer physicians. Four of the scales have alphas of .80 or greater; the fifth has an alpha of .74. Thus, all five scales have alpha values conventionally acceptable for research purposes (.70 or greater) (Gadermann, Guhn, and Zumbo 2012, 5), and four of the five (all but the scale for product selection barriers) have alpha results that DeVellis (2012, 109) subjectively rates as "very good."

Table 4. Cronbach's Alpha Results for the Composite Scales

	Cronbach's Alpha	Mean	Standard Deviation
Improved information (5 items)	.87	1.88	0.59
Cost barriers (3 items)	.88	2.34	0.56
Implementation barriers (6 items)	.82	2.09	0.47
Product selection barriers (3 items)	.74	2.06	0.56
HITECH financial incentives (2 items	.80	2.03	0.71

Table 5 presents the resulting correlations among the five scales. Even after grouping the original individual items into these scales there are still statistically significant correlations among the scales, but this is not surprising since the sample size of 1,043 for the population of interest means that even a correlation coefficient of 0.07 will be statistically significant at $p<0.05$, and a correlation coefficient of 0.11 will be statistically significant at $p<0.001$. More substantively, when dealing with underlying constructs such as attitudes or personality traits, it is quite plausible that two such constructs can be correlated even though they represent different concepts (A. B. Anderson, Basilevsky, and Hum 1983, 280). These correlations among the scales do not rise to the 0.80 or 0.90 level that might indicate a multicollinearity issue for modeling purposes (Kennedy 2008, 196).

Table 5. Correlations for Five Scales of EHR Adoption Facilitators or Barriers

	Improved Information	HITECH Incentives	Cost Barriers	Implementation Barriers	Product Selection Barriers
Improved information	1.00				
HITECH incentives	0.51	1.00			
Cost barriers	0.25	0.23	1.00		
Implementation barriers	0.23	0.22	0.47	1.00	
Product selection barriers	0.28	0.19	0.43	0.49	1.00

Note: All correlation results in the table are statistically significant at $p<0.001$.

3.3 Hypotheses

The five composite scales developed above provide an opportunity to test the significance of each of these factors in predicting EHR adoption status. As discussed in Chapter 2, there is existing qualitative literature that would support each of these issues as relevant to EHR adoption among physicians, but the research herein will fill a gap in the literature by systematically testing and comparing the significance of these five factors as predictors of adoption status, using a set of logistic regression models in which the physician's EHR adoption status serves as the dependent variable. Specific hypotheses to be tested with the five composite scales, as shown in italics, are as follows:

- **Hypothesis 1.** The traditional sociological literature on the importance of information in diffusion finds that earlier adopters are more socially integrated in professional networks and are also more active in seeking information about an innovation (Rogers 2003, 298; Coleman, Katz, and Menzel 1966). *As a result, a reasonable hypothesis would be that physicians who attach more importance to* *improved information for their EHR adoption decision would be more likely than other physicians to have already adopted an EHR.*

- **Hypothesis 2.** Prior to the HITECH Act, most U.S. physicians had poor financial incentives for EHR adoption, as described in Chapter 2. *Therefore, one would expect the importance physicians attach to the HITECH financial incentives to be a significant predictor of adoption status among physicians who had not already adopted prior to the launch of the incentives program, with physicians who view the HITECH incentives as more important being more likely to have adopted than physicians who view the incentives as less important.*
- **Hypothesis 3.** Because the physician EHR market has lacked a dominant design or sufficient standards to ensure interoperability, as described in Chapter 2 the literature on diffusion of network technologies would predict that many would-be adopters would delay a decision to adopt due to uncertainty about which specific EHR product to acquire. The composite scale for barriers related to selecting a specific EHR product includes questions that ask how much a decision on whether to adopt was influenced by having to find an EHR that meets the practice's needs or having to reach consensus within the practice to select an EHR, as well as the general effort needed to select an EHR. While these questions do not explicitly raise the issue of interoperability, they ask whether it is or was a challenge to select a specific EHR, which is what the network effects theory would expect in the absence of interoperability or a dominant design. *Thus, the composite scale for product selection barriers can be used to test the hypothesis*

that reporting challenges in selecting a specific EHR would be a significant predictor of adoption status, with physicians who report this issue as a larger barrier being less likely than other physicians to have adopted yet.

- **Hypothesis 4.** *Given the literature cited in Chapter 2 on the significant financial costs associated with EHR adoption, it is reasonable to expect that the more physicians report cost issues as an adoption barrier the less likely they are to have adopted to date.*
- **Hypothesis 5.** Similarly, Chapter 2 indicates there is much literature on the complexity and challenges of actually implementing an EHR system from an operational perspective. *Thus it is reasonable to expect that physicians who report greater implementation concerns would be less likely to have adopted to date.*

Further, because the HITECH Act includes provisions intended to address many of these issues, there is also value in testing whether the significance of each of these various adoption factors differs for those adoption decisions occurring since implementation of HITECH. The HITECH Act was passed in 2009, so for purposes of defining EHR adoption decisions that could have been influenced by HITECH, one approach described below includes those physicians who started using an EHR in 2010 or later, as well as non-adopters. A second approach described below isolates those physicians who, at the time of the 2011 survey, were not yet using an EHR but were in the process of adoption (defined as either in the midst of purchasing an EHR or had already purchased one but not yet using it). A third approach described below more narrowly focuses on physicians who were non-adopters in the 2011 survey, and then tests which factors are significant for predicting who changed status in 2012 to be a new adopter.

3.4 Statistical models

The hypotheses above on factors influencing EHR adoption decisions can be tested using a set of logistic regression models. All five composite scales are tested in each model, but multiple model versions are specified because there are several issues that merit sensitivity testing. First, as described below, three types of models are presented to test alternative specifications for the dependent variable of EHR adoption status (model types 1, 2, and 3). Second, for model types 1 and 2, there is further variation based on whether or not pre-HITECH adopters are included in the data. Third, for the simplest model type, which is less sensitive to sample size, one more variation tests the sensitivity of the results when the data are limited to physicians in solo and two-physician practices, for reasons discussed below. Thus, six models are ultimately specified, and the differences among their specifications are discussed below and summarized in Table 6.

Model type 1 is a cross-sectional logistic regression with a binary dependent variable for whether or not the physician is using an EHR as of the 2011 survey. Three versions of this model vary by the physicians included in the model. Model 1a includes the core population identified for the analysis: physician respondents in practices that are owned by physicians (rather than by a hospital, HMO, etc.) and the practice size is not larger than 10 physicians. As discussed above, these two filters are intended to minimize a key risk of measurement error by excluding physician respondents in large practices or practices owned by large organizations (HMOs, hospitals, etc.), since these individual respondents would seem unlikely to have sufficient knowledge of which factors were or were not influential to the decision-making on EHR adoption for their practice. A second version of this model, model 1b, conducts a sensitivity test by excluding those physicians who adopted an EHR prior to 2010 -- the year the HITECH incentive program details were announced. A third version of this model, model 1c, limits respondents to physicians in solo and two-physician practices, to test whether the results vary for the smallest size practices, whose EHR adoption rate has lagged the most (Decker, Jamoom, and Sisk 2012). Also, with these one- and two-physician practices one can be even more confident that the respondents are knowledgeable about the practice's decision-making with respect to EHR adoption.

Model 2a is still a cross-sectional model using the same 2011 data and the same independent variables as model 1a, but model 2a uses multinomial logistic regression for a more nuanced, three-category definition of adoption status in the dependent variable: 1) physicians who are using an EHR as of 2011, 2) physicians who are in the process of adopting as of 2011 (defined as those in the midst of purchasing an EHR and those who already purchased but are not yet using it), and 3) physicians who are not yet in-process. Like model 1b, model 2b again tests the sensitivity of excluding those physicians who adopted an EHR prior to 2010 -- the year the HITECH incentive program details were announced.

Table 6. Matrix of Alternative Model Specifications

All models test the 5 composite scales reflecting physician-reported adoption facilitators/barriers; all models also include control variables for physician characteristics*				
Model	**Dependent Variable**	**Population**	**Observations (Physician Respondents)**	**Rationale**
Model Type 1: Cross-sectional data, logistic regression	Binary adoption status in 2011 (0= Not an EHR user, 1=EHR user)			Straightforward model and dependent variable definition of adoption
Model 1a. Base case population		Physician respondents in physician-owned practices of <=10 physicians	1,043	Larger sample size, respondents likely knowledgeable on adoption decision
Model 1b. Sens. test on population		Excluding those using an EHR before 2010	663	Focuses on adoption during HITECH period
Model 1c. Sens. test on population		Limit to physician-owned practices of 1-2 physicians	522	Very high confidence in respondents' knowledge on adoption decision
Model Type 2: Cross-sectional data, multinomial logistic regression	3 categories of 2011 adoption status (0=Not yet in process, 1=In process, 2=EHR user)**			More nuanced definition of adoption status for the dependent variable
Model 2a. Base case population		Same as 1a	1,043	Same as 1a, but more nuanced dependent variable
Model 2b. Sens. test on population		Same as 1b	663	Same as 1b, but more nuanced dependent variable
Model Type 3: Longitudinal data, logistic regression	Binary adoption status in 2012, given non-user status in 2011 (0=Not a user in 2012, 1=User in 2012)	2011 non-users who are also respondents in the 2012 survey, subject to the population criteria from model 1a	383	Longitudinal approach controls for unmeasured time-invariant respondent characteristics

* Control variables include: physician specialty (primary care, surgical, other), number of physicians in the practice, physician age, location in a metropolitan statistical area (MSA),U.S. Census region (northeast, south, midwest, west), and the number of NAMCS-eligible physicians in the state.
** "In process" defined here as the sum of: 1) those in the process of selecting an EHR system, plus 2) those who already purchased a system but were not yet using it.

Model type 3 is a longitudinal model that uses the same independent variables as Models 1 and 2 but the survey respondents are limited to those who responded to both the 2011 and 2012 survey rounds and were non-users in 2011. This logistic regression model then tests how significant each of the five types of facilitators/barriers are in discriminating between the 2011 non-users who stayed as non-users versus those who changed status to become users in 2012, based on what the physicians reported about those facilitators/barriers in 2011 – before any of them became EHR users.

In addition to the composite scales, the models also include additional explanatory variables to control for the following physician characteristics:

1. physician specialty (primary care, surgical, other specialty),
2. number of physicians in the practice (1, 2, 3-5, 6-10),
3. physician age (under 35, 35-44, 45-54, 55-65, 65 and over),
4. whether the practice is located in a Metropolitan Statistical Area (MSA),
5. U.S. Census region (northeast, south, midwest, west), and
6. the number of physicians in the state.

The first five of these control variables reflect physician attributes that are commonly included in quantitative studies of EHR adoption among physicians (Decker, Jamoom, and Sisk 2012; Hsiao and Hing 2014; Jamoom et al. 2014) Along with the MSA variable, the number of NAMCS survey-eligible physicians in each respondent's state is included to allow for the possibility that adoption is positively related to the number of potential adopters in an area, as might be predicted by two diffusion theories described in Chapter 2 -- social contagion and network effects. Other than the census region variable included above, it was not possible to include a less aggregated variable that more directly linked different states in proximity because, for privacy reasons, NCHS masked the state identity in the survey's state variable. For the same reason, several of the other variables above are available as categorical rather than continuous data, including practice size and physician age.

All of the categorical variables are modeled using dummy variables. While the selection of the reference category for dummy variables is sometimes an arbitrary decision and generally does not influence the results, a brief explanation of the reference category choices is useful. For the physician specialty variable, primary care was selected as the reference category because it is the largest category in the data and it is intuitive to compare primary care physicians to different types of specialists (as is common in the literature). For the number of physicians in the practice, solo practice was selected as the reference category because it is the largest category in the data and again it is intuitive to compare other practice sizes to the smallest practices. For physician age, age 55-64 was selected as the reference category because it was the largest category in the data. For the MSA variable, the reference category was physicians who are not located in an MSA, to allow an intuitive interpretation of the impact of being in an MSA. For region, given that all four regions are well represented in the data, northeast served as the reference category simply as the arbitrary default in Stata due to the codes for this variable.

Tables 7 through 12 present summary statistics for the data used in each of the models described above.

Table 7. Summary Statistics for Variables in Model 1a

(2011 data for physicians in physician-owned practices of size <=10)

	Obs.	Unwtd Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd Mean* (and Std. Error)
EHR adoption status	1,043	0.47	0.50	0	1	100.0%	0.43
0= Non-user	556					57.0%	(0.03)
1= User	487					43.0%	
Improved information	1,043	1.88	0.59	1.00	3.00	NA	1.94 (0.03)
HITECH incentives	1,043	2.03	0.71	1.00	3.00	NA	2.05 (0.04)
Cost barriers	1,043	2.34	0.56	1.00	3.00	NA	2.37 (0.03)
Implementation barriers	1,043	2.09	0.47	1.00	3.00	NA	2.11 (0.02)
Product selection barriers	1,043	2.06	0.56	1.00	3.00	NA	2.04 (0.03)
Physician specialty	1,043	NA	NA	1	3	100.0%	NA
1= Primary care	522					50.3%	
2= Surgical	244					21.9%	
3= Other specialty	277					27.8%	
Located in an MSA	1,043	0.77	0.42	0	1	100.0%	0.90
0=No	235					10.4%	(0.01)
1=Yes	808					89.6%	
Practice size (no. of physicians)	1,043	NA	NA	1	4	100.0%	NA
1= 1	406					42.3%	
2= 2	116					13.2%	
3= 3-5	323					27.3%	
4= 6-10	198					17.2%	
Region	1,043	NA	NA	1	4	100.0%	NA
1= Northeast	198					23.3%	
2= Midwest	217					16.4%	
3= South	346					36.7%	
4= West	282					23.7%	
Physician age	1,043	NA	NA	1	5	100.0%	NA
1= <35	16					0.7%	
2= 35-44	187					17.7%	
3= 45-54	309					28.2%	
4= 55-64	395					38.7%	
5= 65+	136					14.8%	
Number of NAMCS-eligible physicians in the state (000s)	1,043	6.76	7.63	0.52	39.84	NA	17.55 (0.78)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.

Source: Author's analysis of the 2011 NAMCS Physician Workflow Supplement

Table 8. Summary Statistics for Variables in Model 1b
(2011 data for physicians in physician-owned practices of size <=10, excluding pre-2010 EHR users)

	Obs.	Unwtd Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd. Mean* (and Std. Error)
EHR adoption status	663	0.16	0.37	0	1	100.0%	0.14
0= Non-user	556					86.3%	(0.02)
1= User	107					13.7%	
Improved information	663	2.05	0.58	1.00	3.00	NA	2.11 (0.04)
HITECH incentives	663	2.22	0.63	1.00	3.00	NA	2.25 (0.04)
Cost barriers	663	2.44	0.53	1.00	3.00	NA	2.46 (0.04)
Implementation barriers	663	2.18	0.45	1.00	3.00	NA	2.20 (0.03)
Product selection barriers	663	2.14	0.56	1.00	3.00	NA	2.11 (0.04)
Physician specialty	663	NA	NA	1	3	100.0%	NA
1= Primary care	296					43.9%	
2= Surgical	165					24.2%	
3= Other specialty	202					31.9%	
Located in an MSA	663	0.78	0.42	0	1	100.0%	0.90
0= No	146					10.2%	(0.01)
1= Yes	517					89.8%	
Practice size (no. of physicians)	663	NA	NA	1	4	100.0%	NA
1= 1	308					52.8%	
2= 2	74					11.1%	
3= 3-5	181					23.3%	
4= 6-10	100					12.7%	
Region	663	NA	NA	1	4	100.0%	NA
1= Northeast	128					21.5%	
2= Midwest	135					16.3%	
3= South	239					39.0%	
4= West	161					23.3%	
Physician age	663	NA	NA	1	5	100.0%	NA
1= <35	10					0.6%	
2= 35-44	110					15.8%	
3= 45-54	172					26.7%	
4= 55-64	271					39.8%	
5= 65+	100					17.1%	
Number of NAMCS-eligible physicians in the state (000s)	663	6.84	7.66	0.52	39.84	NA	17.82 (1.05)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.
Source: Author's analysis of the 2011 NAMCS Physician Workflow Supplement

Table 9. Summary Statistics for Variables in Model 1c

(2011 data for physicians in physician-owned practices of size <=2)

	Obs.	Unwtd Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd. Mean* (and Std. Error)
EHR adoption status	522	0.34	0.48	0	1	100.0%	0.32
0=Non-user	342					68.0%	(0.04)
1=User	180					32.0%	
Improved information	522	1.89	0.60	1.00	3.00	NA	1.97 (0.05)
HITECH incentives	522	1.96	0.71	1.00	3.00	NA	2.04 (0.05)
Cost barriers	522	2.41	0.56	1.00	3.00	NA	2.47 (0.04)
Implementation barriers	522	2.11	0.48	1.00	3.00	NA	2.16 (0.03)
Product selection barriers	522	2.02	0.58	1.00	3.00	NA	2.04 (0.04)
Physician specialty	522	NA	NA	1	3	100.0%	NA
1= Primary care	241					45.7%	
2= Surgical	119					20.7%	
3= Other specialty	162					33.7%	
Located in an MSA	522	0.76	0.43	0	1	100.0%	0.90
0= No	126					9.8%	(0.01)
1= Yes	396					90.2%	
Practice size (no. of physicians)	522	NA	NA	1	2	100.0%	NA
1= 1	406					77.8%	
2= 2	116					22.2%	
Region	522	NA	NA	1	4	100.0%	NA
1= Northeast	106					25.8%	
2= Midwest	92					14.7%	
3= South	180					34.5%	
4= West	144					25.0%	
Physician age	522	NA	NA	1	5	100.0%	NA
1+2= <35 + 35-44 **	69					12.7%	
3= 45-54	145					27.1%	
4= 55-64	225					40.7%	
5= 65+	83					19.5%	
Number of NAMCS-eligible physicians in the state (000s)	522	7.25	8.15	0.52	39.84	NA	18.49 (1.12)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.

** The <35 and 35-44 age categories are combined in this table because for this model one of these age categories has a cell size smaller than what NCHS's non-disclosure rules allow for display purposes. These two age categories were still modeled as separate dummy variables in the actual analysis.

Source: Author's analysis of the 2011 NAMCS Physician Workflow Supplement

Table 10. Summary Statistics for Variables in Model 2a
(2011 data for physicians in physician-owned practices of size <=10)

	Obs.	Unwtd. Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd. Mean* (and Std. Error)
EHR adoption status	1,043	NA	NA	0	1	100.0%	NA
0=Not yet in process	409					39.1%	
1=In process of adopting	147					17.9%	
2=User	487					43.0%	
Improved information	1,043	1.88	0.59	1.00	3.00	NA	1.94 (0.03)
HITECH incentives	1,043	2.03	0.71	1.00	3.00	NA	2.05 (0.04)
Cost barriers	1,043	2.34	0.56	1.00	3.00	NA	2.37 (0.03)
Implementation barriers	1,043	2.09	0.47	1.00	3.00	NA	2.11 (0.02)
Product selection barriers	1,043	2.06	0.56	1.00	3.00	NA	2.04 (0.03)
Physician specialty	1,043	NA	NA	1	3	100.0%	NA
1= Primary care	522					50.3%	
2= Surgical	244					21.9%	
3= Other specialty	277					27.8%	
Located in an MSA	1,043	0.77	0.42	0	1	100.0%	0.90
0= No	235					10.4%	(0.01)
1= Yes	808					89.6%	
Practice size (no. of physicians)	1,043	NA	NA	1	4	100.0%	NA
1= 1	406					42.3%	
2= 2	116					13.2%	
3= 3-5	323					27.3%	
4= 6-10	198					17.2%	
Region	1,043	NA	NA	1	4	100.0%	NA
1= Northeast	198					23.3%	
2= Midwest	217					16.4%	
3= South	346					36.7%	
4= West	282					23.7%	
Physician age	1,043	NA	NA	1	5	100.0%	NA
1= <35	16					0.7%	
2= 35-44	187					17.7%	
3= 45-54	309					28.2%	
4= 55-64	395					38.7%	
5= 65+	136					14.8%	
Number of NAMCS-eligible physicians in the state (000s)	1,043	6.76	7.63	0.52	39.84	NA	17.55 (0.78)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.
Source: Author’s analysis of the 2011 NAMCS Physician Workflow Supplement

Table 11. Summary Statistics for Variables in Model 2b
(2011 data for physicians in physician-owned practices of size <=10, excluding pre-2010 EHR users)

	Obs.	Unwtd. Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd. Mean* (and Std. Error)
EHR adoption status	663	NA	NA	0	1	100.0%	NA
0=Not yet in process	409					59.2%	
1=In process of adopting	147					27.1%	
2=User	107					13.7%	
Improved information	663	2.05	0.58	1.00	3.00	NA	2.11 (0.04)
HITECH incentives	663	2.22	0.63	1.00	3.00	NA	2.25 (0.04)
Cost barriers	663	2.44	0.53	1.00	3.00	NA	2.46 (0.04)
Implementation barriers	663	2.18	0.45	1.00	3.00	NA	2.20 (0.03)
Product selection barriers	663	2.14	0.56	1.00	3.00	NA	2.11 (0.04)
Physician specialty	663	NA	NA	1	3	100.0%	NA
1= Primary care	296					43.9%	
2= Surgical	165					24.2%	
3= Other specialty	202					31.9%	
Located in an MSA	663	0.78	0.41	0	1	100.0%	0.90
0= No	146					10.2%	(0.01)
1= Yes	517					89.8%	
Practice size (no. of physicians)	663	NA	NA	1	4	100.0%	NA
1= 1	308					52.8%	
2= 2	74					11.1%	
3= 3-5	181					23.3%	
4= 6-10	100					12.7%	
Region	663	NA	NA	1	4	100.0%	NA
1= Northeast	128					21.5%	
2= Midwest	135					16.3%	
3= South	239					39.0%	
4= West	161					23.3%	
Physician age	663	NA	NA	1	5	100.0%	NA
1= <35	10					0.6%	
2= 35-44	110					15.8%	
3= 45-54	172					26.7%	
4= 55-64	271					39.8%	
5= 65+	100					17.1%	
Number of NAMCS-eligible physicians in the state (000s)	663	6.84	7.66	0.52	39.84	NA	17.82 (1.05)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.
Source: Author's analysis of the 2011 NAMCS Physician Workflow Supplement

Table 12. Summary Statistics for Variables in Model 3
(Physicians in physician-owned practices of size <=10, non-users in 2011 who also responded in the 2012 survey round)

	Obs.	Unwtd. Mean*	Std. Dev.	Min	Max	Pop. Wtd. Distribution, for Categorical Variables	Wtd. Mean* (and Std. Error)
2012 EHR adoption status	383	0.22	0.41	0	1	100.0%	0.22
(among 2011 non-users)							(0.04)
0= Non-user in 2012	299					77.6%	
1= User in 2012	84					22.4%	
Improved information	383	2.13	0.55	1.00	3.00	NA	2.17 (0.05)
HITECH incentives	383	2.18	0.62	1.00	3.00	NA	2.19 (0.04)
Cost barriers	383	2.48	0.51	1.00	3.00	NA	2.45 (0.05)
Implementation barriers	383	2.21	0.45	1.00	3.00	NA	2.21 (0.04)
Product selection barriers	383	2.17	0.56	1.00	3.00	NA	2.14 (0.04)
Physician specialty	383	NA	NA	1	3	100.0%	NA
1= Primary care	164					39.0%	
2= Surgical	101					24.6%	
3= Other specialty	118					36.4%	
Located in an MSA	383	0.78	0.41	0	1	100.0%	0.89
0= No	84					10.5%	(0.02)
1= Yes	299					89.5%	
Practice size (no. of physicians)	383	NA	NA	1	4	100.0%	NA
1= 1	179					48.8%	
2= 2	46					11.8%	
3= 3-5	100					26.5%	
4= 6-10	58					13.0%	
Region	383	NA	NA	1	4	100.0%	NA
1= Northeast	73					22.2%	
2= Midwest	80					16.5%	
3= South	135					38.6%	
4= West	95					22.8%	
Physician age	383	NA	NA	1	5	100.0%	NA
1+2= <35 + 35-44 **	59					13.4%	
3= 45-54	105					27.0%	
4= 55-64	168					43.4%	
5= 65+	51					16.2%	
Number of NACMS-eligible physicians in the state (000s)	383	6.83	7.57	0.52	39.84		17.73 (1.42)

* Mean values are not applicable for categorical data with more than 2 categories; see distributions instead.

** The <35 and 35-44 age categories are combined in this table because for this model one of these age categories has a cell size smaller than what NCHS's non-disclosure rules allow for display purposes. These two age categories were still modeled as separate dummy variables in the actual analysis.

Source: Author's analysis of the 2011 NAMCS Physician Workflow Supplement

3.5 Additional data sources

While the Physician Workflow survey data comprise the core data for this research, additional data will support specific sections of the dissertation. In particular, Chapter 4 will discuss the evolution of federal policy to promote health IT diffusion based on the following qualitative data sources:

- the 2004 executive order establishing ONCHIT,
- health IT legislation and associated committee reports,
- the Congressional Record,
- media coverage of health IT policy developments (both newspapers and trade press),
- HITECH implementation regulations and supporting documents,
- administrative data for the Meaningful Use financial incentives program,
- reports on EHR interoperability by federal science and technology panels,
- public documents from advocacy groups, and
- ONCHIT advisory committee documents.

3.6 Recap of approach

The core of this dissertation is a statistical analysis of 2011 and 2012 survey data to quantify and compare the extent to which different types of adoption facilitators and barriers reported by physicians predict their status as EHR adopters or non-adopters. Five composite scales representing different types of adoption facilitators and barriers were developed from more specific survey items, and the significance of these scales in predicting the dependent variable of adoption status can be tested with a set of logistic regression models. Multiple model versions are specified to provide sensitivity analysis across multiple dimensions.

Prior to presenting the results of this quantitative analysis, however, it is useful to provide more detailed background on key developments in federal policy to promote diffusion of EHRs. Chapter 4 provides this context.

Chapter 4. Key Developments In Federal Policy To Promote Health IT

While the 2009 passage of the Health Information Technology for Economic and Clinical Health (HITECH) Act is the most important development to date in federal policy to promote health IT, an important first step towards that milestone was the Bush administration's 2004 establishment of the Office of the National Coordinator for Health IT (ONCHIT, or simply ONC) within the Department of Health and Human Services. At the time he announced the establishment of ONC, President Bush also announced a goal that every American should have a personal EHR within 10 years (Bush 2004). However, after establishing ONC, for the remainder of his presidency Bush did not make health IT a policy priority, as the administration appeared to favor a very modest federal role. Bush never proposed major health IT legislation to support his stated 10-year objective, and as discussed below, even when multiple health IT bills were in play in Congress, the Bush administration did not aggressively act to support any specific bill.

ONC's initial budget and authority gave no hint of the influence that would subsequently arise with the HITECH Act. Instead, the executive order which established ONC focused the office's mission on developing and directing implementation of a strategic plan "to guide the nationwide implementation of interoperable health information technology in both the public and private sectors" (Executive Order 13335 of April 27 2004, 24059). Executive Order 13335 (2004, 24060) called for the plan to:

- advance the development, adoption, and implementation of national health IT standards "through collaboration among public and private interests;"
- address technical, scientific, economic, and other issues affecting health IT adoption;
- evaluate evidence on the benefits and costs of health IT, including which stakeholders would incur any benefits and costs;
- address privacy and security issues associated with interoperable health IT; and
- include measurable outcome goals.

Tellingly, Bush's executive order (2004, 24060) also instructed ONC not to assume additional federal resources or spending.

As a result, during the remainder of the Bush administration ONC focused on low-key technical activities such as promoting standards for health IT interoperability and the early planning of a national health information network. For example, ONC contracted with the American National Standards Institute (ANSI) to establish a Health Information Technology Standards Panel (HITSP) to begin coordination with health IT vendors and other stakeholders (Congressional Budget Office 2008). However, many other entities were also working on health IT standards for various constituencies, so the HITSP was hardly the only actor in the standard-setting process (Hammond 2005). ONC also worked with industry to establish a Certification Commission for Healthcare Information Technology (CCHIT), which would certify vendors' health IT products for compliance with HITSP standards (Congressional Budget Office 2008).

4.1 Support for a more aggressive federal policy intervention

In addition to the establishment of ONC, a second important precursor to the HITECH Act was the 2005 release of a series of health IT studies and related journal articles by a team of analysts at the RAND Corporation, which collectively presented an argument for more aggressive federal policies to promote health IT diffusion. RAND weighed in on several related fronts. Fonkych and Taylor (2005) described the current levels of health IT adoption in the U.S., characteristics of early adopters and non-adopters, and potential barriers to adoption. Bigelow et al. (2005) studied complementary health care interventions that potentially could yield large improvements in population health and associated health care cost savings, such as patient safety improvements, greater emphasis on preventive care, disease management, and promotion of healthier lifestyles. Probably most important were two summary articles by RAND in *Health Affairs*, a leading health policy journal. These articles, by Hillestad et al. (2005) and Taylor et al. (2005), together presented RAND's estimate that full, effective adoption of health IT would ultimately save more than $80 billion per year if accompanied by innovations to identify and reward high-quality, efficient providers – and perhaps several times that amount if health IT adoption were accompanied by the other types of broad interventions described in the study by Bigelow et al.

The RAND analysts described their estimates as "potential" savings, because "in general, the currently useful evidence is not robust enough to make strong predictions" (Hillestad et al. 2005, 1104). This might seem a reasonable caveat on the surface, but it also seems to rationalize a key methodological decision by the RAND team to base its assumptions only on literature that showed at least some positive impact of health IT on health care or administrative costs, while interpreting literature with "negative or no effect of health IT as likely being attributable to ineffective or not yet effective implementation" (Hillestad et al. 2005, 1105). Thus, the RAND findings were biased by an up-front presumption that health IT would ultimately cause savings, and the question became simply how large those savings would be. When multiplying percentage savings against an expenditure baseline as large as the U.S. health care system, even a modest percentage savings can amount to significant absolute dollars.

In addition to the RAND estimates, a study by Walker et al. (2005) from the Center for Information Technology Leadership (CITL) also estimated approximately $80 billion in savings from full implementation of health IT, but based on a different rationale and methodology than RAND's analysis. While RAND's low-end savings estimate of approximately $80 billion was based primarily on health IT efficiencies which would lower providers' internal costs (which would then be recaptured via provider reimbursement reforms), the CITL study's estimated savings were attributable primarily to increased efficiency in coordinating care across providers (e.g., eliminating duplicate tests). Favorable reports on EHR impacts in the Veterans Health Administration also contributed to a growing interest in EHRs in health policy circles, despite the point discussed in Chapter 2 that as a large, vertically integrated health plan, the VHA was not especially representative of the vast bulk of U.S. physicians and hospitals (A. Jha et al. 2003; Asch et al. 2004).

Notwithstanding the concerns above about the RAND estimates or the generalizability of early adopter experience, the RAND research provided an influential business case for those policy entrepreneurs advocating a major federal intervention to promote health IT adoption, especially coupled with the favorable narrative on the VHA experience. In addition to this analytical justification, health IT also offered leaders in both major political parties a chance to voice support for a type of health system reform that generally was not viewed as divisive or threatening – an important political consideration after the bruising health reform debates of the early Clinton administration and then the emerging backlash by patients and medical providers against managed care insurance plans in the late 1990's. As a more technocratic policy issue, health IT also offered an opportunity for bipartisanship. For example, former Republican Speaker of the House Newt Gingrich, who founded a Center for Health Transformation to advocate for EHR adoption among other health system reforms, and Senator Hillary Clinton (D-NY) drew media attention when they put aside past conflicts to partner in supporting one of the many health IT bills introduced in the 109th Congress in 2005 (Stone 2005). Lobbying by EHR vendors also ramped up during this period, especially through the industry's main trade association, the Health Information Management and Systems Society (HIMSS) (O'Harrow 2009; Creswell 2013).

With this rising advocacy for health IT, the Senate passed the Wired for Health Care Quality Act (S. 1418) by unanimous consent in November 2005, with a bipartisan list of key supporters including Republicans Bill Frist (R-TN) and Mike Enzi (R-WY) along with Democrats Edward Kennedy (D-MA) and Hillary Clinton (D-NY). Frist's interest was especially significant given his position as Senate Majority Leader and his background as a physician whose father had founded a large chain of for-profit hospitals. The House then passed its own bill, the Health Information Technology Promotion Act (H.R. 4157) sponsored by the Ways and Means Health Subcommittee Chair Nancy Johnson (R-CT), by a 270-148 vote in July 2006. As part of their justification for federal intervention, supporters of both the House and Senate bills explicitly cited the RAND studies as well as the earlier Institute of Medicine reports on quality and patient safety issues (Wired for Health Care Quality Act 2005; Health Information Technology Promotion Act 2006). However, while the two bills were similar on certain issues, such as permanently establishing ONCHIT, the bills also differed in several respects. The House bill included updates to health data privacy rules originally defined in the Health Insurance Portability and Accountability Act of 1996, while the Senate bill had more extensive provisions on certification of commercial EHR products. Both bills included modest grant programs for certain categories of EHR adopters, but they differed on the target populations for the grants and other details. While both bills included annual funding authorization for grant programs to promote EHR adoption, at $100 million to $150 million per year this authorized funding would have been nowhere near the level of investment indicated by RAND’s analysis of subsidy options (U.S. House, Committee on Energy and Commerce 2008, 33; Congressional Budget Office 2005; Congressional Budget Office 2006). The Bush administration declined to actively push for either of these bills, and the respective versions passed by the House and Senate never went to conference.

In the 110th Congress (in session 2007-2008), the Senate bill was reintroduced and reported out of the HELP committee but made no further progress. A new House bill, the PRO(TECH)T Act (H.R. 6357) was reported out of the Energy and Commerce Committee but also made no further progress. In addition to difficulties in reconciling provisions of the different bills amidst other Congressional priorities (e.g., the Iraq war and the Hurricane Katrina recovery), passage of a health IT bill became significantly more difficult in the 110th Congress because Democrats re-instated the so-called "PAYGO" rule when they regained control of the House and Senate in January 2007 (Conn 2007). PAYGO required spending increases to be offset by spending cuts or revenue increases to avoid a net increase in the federal deficit, and the Congressional Budget Office (CBO) had estimated that the major health IT bills under consideration would increase federal spending in net (Tax Policy Center 2007; Congressional Budget Office 2005; Congressional Budget Office 2006).

In response to a request from the Chairman of the Senate Budget Committee, CBO (2008) then weighed in with a more in-depth, stand-alone report on health IT in May 2008, including a review of the existing health IT literature concerning benefits and costs, barriers to adoption, and options for federal policy interventions. CBO noted the issues discussed above with the RAND report and also raised a series of more technical criticisms on the details of specific assumptions and calculations in both the RAND and CITL studies. Ultimately, CBO's findings were mixed with respect to whether health IT would ultimately achieve significant health care cost savings. CBO explained the many theoretical arguments for positive impacts from health IT, but tempered this discussion by noting the very limited and mixed empirical evidence on actual impacts.

In September 2008 Representative Pete Stark, Chairman of the House Ways and Means Committee's Subcommittee on Health, introduced a new health IT bill, the Health-e Information Technology Act (H.R. 6898), which included Medicare incentive payments and penalties to promote EHR adoption – the incentive approach subsequently included in the HITECH Act (Stark 2008). With the onset of the economic crisis and the rapidly approaching 2008 election, however, there was no specific action taken on Stark's bill either.

Thus, during this 2005-2008 period, there was meaningful Congressional interest in health IT, but the multiple bills in play differed on numerous policy details and the Bush administration declined to throw its weight behind any specific bill. With no action-forcing event and amidst competing priorities and budget constraints, health IT was not an urgent enough priority to command legislative resolution.

4.2 The HITECH Act

With this preamble, two events in the fall of 2008 greatly increased political momentum for Congressional action on health IT. First, Democrats gained the White House while increasing their majority in both chambers of Congress, and health system reform was a central element of the Democratic agenda. Second, the economic crisis spurred interest in federal investments that could be quickly included in omnibus fiscal stimulus legislation. John Kingdon (2010) describes how a back-burner issue can rise on the agenda for sudden action when problem, policy, and political streams converge during a window of opportunity, and inclusion of the HITECH Act in the American Recovery and Reinvestment Act that passed in February 2009 is a vivid example of Kingdon's model.

The RAND and CITL studies, as well as the literature touting positive EHR impacts for the Veterans Health Administration and Kaiser Permanente, had already provided the analytical rationale for a large federal investment in health IT adoption. Health system reform was a key Democratic campaign promise, and diffusion of health IT was widely viewed as a foundational step towards a range of broader innovations (Blumenthal 2011). From a tactical perspective, the rush to craft the fiscal stimulus bill created a brief window of opportunity to attach, with little debate, EHR funding that was orders of magnitude larger than the earlier, unsuccessful health IT bills. Former Senate Majority Leader Tom Daschle, a key health policy advisor to President Obama and his nominee to be Secretary of HHS, was a strong supporter of health IT who argued within the Obama transition team for inclusion of EHR subsidies within the stimulus package (O'Harrow 2009). Meanwhile, HIMSS, the health IT trade association, lobbied for the stimulus bill to include a minimum of $25 billion in funding for EHR adoption subsidies (Lieber and Christian 2008; Lieber 2009); CBO (2009) ultimately estimated the direct cost of the subsidy program included in the HITECH Act at $32.7 billion through 2019 (including an offset for penalties charged to non-adopters). The HIMSS rhetoric to support this investment touted not only health system benefits from EHR adoption but also the purported job creation that would result from this federal spending (Lieber and Christian 2008; Lieber 2009). The president of the HIMSS health IT trade association characterized the circumstances supporting passage of the HITECH Act as “perhaps a once-in-a-lifetime opportunity to make something happen”(O’Harrow 2009).

David Blumenthal, an Obama advisor who was appointed the next National Coordinator for HIT shortly after passage of the HITECH Act, also points to the momentum of the broader stimulus package as critical to the scope of the HITECH Act. According to Blumenthal (2011, 2325), the political will for a major investment in health IT had not existed previously, but that the economic crisis “broke the logjam.” Also consistent with the Kingdon model, Blumenthal (2011, 2325) notes that because of the earlier, stalled health IT bills, “Congress was well prepared to respond to the opportunity created by the Obama administration’s support for health information technology and the momentum of the stimulus bill. The HITECH Act was drafted in a matter of weeks.”

The HITECH Act includes the following major provisions:

- The law permanently established the Office of the National Coordinator for Health IT (ONC) within the Department of Health and Human Services (HHS); ONC had previously existed only by executive order. The law also provided $2 billion in one-time discretionary funding to launch a range of ONC programs and operations (Blumenthal 2011).
- The law established a multi-year program of Medicare and Medicaid incentive payments for physicians and hospitals who demonstrate “meaningful use” of an EHR. This incentive program is formally administered by the Centers for Medicare and Medicaid Services (CMS), with significant input from ONC. Separate standards for meaningful use apply for office-based physicians and for

hospitals. As described below, the standards for meaningful use are being phased in as stages, with the Stage 1 final rule published in 2010 and the Stage 2 final rule published in 2012. The regulation for stage 3 is under development.

- Using a carrot-and stick-approach, after the expiration of the incentive payment program, physicians and hospitals that still have not demonstrated meaningful use of an EHR will face cuts in their Medicare fee levels. Medicaid fee schedules, which are administered by the individual states, would not be cut.
- The law required ONC to develop a certification program for EHRs. As one condition for a health care provider to qualify for the meaningful use incentive payments, the provider's EHR product must have been certified as having the capabilities required for meaningful use.
- The law mandated temporary establishment of regional extension centers (RECs) to provide education and logistical assistance to local medical providers attempting to adopt EHRs. This program is modeled on the Department of Agriculture's extension program which provided technical support to local farmers adopting agricultural innovations during much of the 20th century. ONC has funded 62 RECs across the nation at a total multi-year program expenditure of $774 million, including learning dissemination activities in addition to direct grants to the individual REC organizations (Lynch et al. 2014). After a one-year extension, the program is due to end in 2015 (Office of the National Coordinator of Health Information Technology 2014, 16).

- The law established two important committees to make recommendations to the National Coordinator: the HIT Policy Committee and the HIT Standards Committee. Both committees have a large membership intended to represent a range of stakeholders including multiple federal agencies, EHR vendors, health care providers, and patient advocacy organizations.
- The law called for ONC to provide grants to states and communities for promotion of health data exchange.
- The law required ONC to support universities and community colleges in expanding the health IT workforce.
- The law increases penalties for negligent breaches of protected health information (PHI) and calls for ONC to propose new approaches to ensure patient privacy.

The financial incentive program is certainly the highest profile component of the HITECH Act. For the Medicare incentive program for physicians, office-based physicians can receive up to $43,720 in EHR incentive payments spread over 5 years if they qualify for each defined stage of meaningful use, starting with eligibility for Stage 1 payments in 2011, as shown in Table 13 below (Centers for Medicare and Medicaid Services 2014c).[7] The maximum payments are reduced for later adopters, and physicians who did not qualify for at least Stage 1 of meaningful use before the end of 2014 will not qualify for any incentive payments. Further, starting in 2015, eligible professionals who have not demonstrated at least Stage 1 of Meaningful Use will face a 1% cut in their Medicare reimbursement rates, growing an additional percentage point for each year they

[7] The maximum amount per physician was originally specified to be $44,000 but was reduced due to budget sequestration.

do not meet Meaningful Use requirements, up to a 5% cut by 2019. Physicians who qualify for the Medicaid version of the incentive program can potentially receive higher payments, up to $63,750 over a six-year period, as shown in Table 14 below (Centers for Medicare and Medicaid Services 2015b). However, the eligibility criteria for the Medicaid version of the incentive program include that at least 30% of the physician's patients must be Medicaid beneficiaries (20% for pediatricians) or the physician must work for a Federally Qualified Health Center (FQHC) or a Rural Health Clinic (RHC) with at least 30% of patients meeting a definition for needy individuals; many physicians do not meet these thresholds. Physicians cannot receive EHR incentive payments from both Medicare and Medicaid, but hospitals can.

Table 13. Schedule of Medicare EHR Incentive Payments for Eligible Professionals

	If First Payment Is Received in:			
	2011	2012	2013	2014
Payment Amount in 2011	$18,000			
Payment Amount in 2012	$12,000	$18,000		
Payment Amount in 2013	$7,840	$11,760	$14,700	
Payment Amount in 2014	$3,920	$7,840	$11,760	$11,760
Payment Amount in 2015	$1,960	$3,920	$7,840	$7,840
Payment Amount in 2016		$1,960	$3,920	$3,920
Total Incentive Payments	**$43,720**	**$43,480**	**$38,220**	**$23,520**

Notes: Eligible professionals who do not demonstrate Meaningful Use by the end of 2014 will not receive any positive incentive payments and instead will face a 1% cut in their Medicare payments in 2015, growing an additional percentage point for each additional year they do not qualify for Meaningful Use, up to a maximum cut of 5% by 2019.

Source: http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Basics.html, accessed March 1, 2015.

Table 14. Schedule of Medicaid EHR Incentive Payments for Eligible Professionals

	If First Payment Is Received in:					
	2011	2012	2013	2014	2015	2016
Payment Amount in 2011	$21,250					
Payment Amount in 2012	$8,500	$21,250				
Payment Amount in 2013	$8,500	$8,500	$21,250			
Payment Amount in 2014	$8,500	$8,500	$8,500	$21,250		
Payment Amount in 2015	$8,500	$8,500	$8,500	$8,500	$21,250	
Payment Amount in 2016	$8,500	$8,500	$8,500	$8,500	$8,500	$21,250
Payment Amount in 2017		$8,500	$8,500	$8,500	$8,500	$8,500
Payment Amount in 2018			$8,500	$8,500	$8,500	$8,500
Payment Amount in 2019				$8,500	$8,500	$8,500
Payment Amount in 2020					$8,500	$8,500
Payment Amount in 2021						$8,500
Total Incentive Payments	**$63,750**	**$63,750**	**$63,750**	**$63,750**	**$63,750**	**$63,750**

Notes: Eligibility criteria for the Medicaid EHR incentive program include that at least 30% of the professional's patients must be Medicaid beneficiaries (20% for pediatricians) or the professional must work for a Federally Qualified Health Center (FQHC) or a Rural Health Clinic (RHC) with at least 30% of patients meeting a definition for needy individuals. Professionals cannot receive EHR incentive payments from both Medicare and Medicaid.

Source: http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/MedicaidStateInfo.html, accessed March 1, 2015.

The incentive program's ultimate cost will depend on provider participation, and, as noted above, CBO (2009) initially estimated the cost of the incentive payments, offset by penalties for non-adopters, at $32.7 billion through 2019. As part of this estimate, CBO assumed the incentive program would increase EHR adoption by 2019 from a counterfactual of 65% of physicians and 45% of hospitals in the absence of the HITECH Act to 90% of physicians and 70% of hospitals under HITECH – a marginal impact on the adoption rate by 2019 of 25 percentage points for both physicians and hospitals.[8]

[8] For a subset of generally rural hospitals known as Critical Access Hospitals, CBO assumed 20% adoption by 2019 in the absence of HITECH and 50% under HITECH.

CBO also assumed that this increased EHR adoption due to the incentives would produce savings on health care services in Medicare and Medicaid, as well as in commercial health insurance costs due to spillover effects, such that the incentive program's net federal budget impact through 2019 (including tax revenue impacts, but excluding off-budget impacts) would be $18.9 billion. In addition to these budgetary impacts associated with the HITECH incentive program, the ARRA also included $2 billion in multi-year funding for programs administered by ONC, such as the Regional Extension Center program and various grants and training programs to promote HIT diffusion (Redhead 2009, 11).

4.3 Implementation to date of the Meaningful Use incentive program

As far as actual experience under the incentive program, through December 2014 426,597 physicians and other professionals (or their employers) had received $10.7 billion worth of incentive payments, representing about 79% of those professionals eligible for the program (Centers for Medicare and Medicaid Services 2015a). Also through December 2014, 4,740 hospitals had received a total of $17.5 billion in adoption payments, representing about 94% of eligible hospitals (Centers for Medicare and Medicaid Services 2015a). Thus, as indicated in Table 15, professionals and hospitals together have collectively received $28.1 billion in incentive payments through December 2014 (Centers for Medicare and Medicaid Services 2015a).

Table 15. EHR Incentive Program Payments Through December 2014

	Medicare only	Medicaid only	Medicare and Medicaid	Total
Professionals (Physicians, etc.) *	$7.3B	$3.4B	NA	$10.7B
Hospitals	$0.7B	$0.4B	$16.4B	$17.5B
Total	$8.0B	$3.8B	$16.4B	$28.1B

* Includes $0.4 billion paid for professionals associated with Medicare Advantage HMOs.

Source: Centers for Medicare and Medicaid Services, http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/DataAndReports.html, accessed February 14, 2015

A central issue for the EHR incentive program is how to define EHR adoption. The HITECH legislation introduced the conceptual requirement for “meaningful use of certified EHR technology,” but Congress left it to federal regulators to determine most of the operational definition for meaningful use. Thus, federal regulations are defining meaningful use of an EHR through a series of stages, where each stage is defined in a separate regulation that specifies a detailed series of functional and operational requirements. Stakeholders including clinicians, EHR vendors, patient advocates, and health policy experts are providing input to regulators via the HIT policy and standards committees mandated by HITECH, as well as the traditional comment process for federal regulations. The final rule formally implementing Meaningful Use Stage 1 was published in 2010, although CMS has subsequently made minor adjustments to the Stage 1 requirements (Centers for Medicare and Medicaid Services 2010a). The final rule implementing Stage 2 was published in 2012 (Centers for Medicare and Medicaid Services 2012a). Stage 3 requirements are still under development, and in August 2014

CMS delayed the start of Stage 3 from January 2016 to January 2017, for providers who qualified for Stage 1 in 2011 or 2012 (the earliest program participants) (Tahir 2014).

As originally implemented, in Stage 1 eligible professionals (primarily physicians) had to satisfy 15 core objectives and five out of 10 "menu objectives", although by 2014 these requirements had been re-arranged slightly and one original requirement had been dropped (capability for electronic exchange of key clinical information with other providers) (Centers for Medicare and Medicaid Services 2010b). As originally implemented, in Stage 1 eligible hospitals had to satisfy 14 core objectives and five out of 10 menu objectives, although by 2014 these requirements had been modified to 11 core objectives and five out of 10 menu objectives (Centers for Medicare and Medicaid Services 2010b). In Stage 2, eligible professionals must satisfy 17 core objectives and three out of six menu objectives, while eligible hospitals must satisfy 16 core objectives and three out of six menu objectives (Centers for Medicare and Medicaid Services 2012b). Stage 2 carries over many objectives from Stage 1, but some of the "menu objectives" from Stage 1 shift to being core objectives (mandatory) for Stage 2. Table 16 summarizes the Stage 1 requirements for professionals, while Table 17 summarizes the Stage 2 requirements.

Table 16. Original Requirements for Physicians and Other Eligible Professionals for Meaningful Use Stage 1

Must Meet 15 Core Objectives *
1. Computerized provider order entry (CPOE)
2, Electronic prescribing of pharmaceuticals
3. Report clinical quality measures (3 core plus 3 elective) *
4. Implement a clinical decision support rule
5. Make health information available to patients electronically
6. Provide patients with clinical summaries of office visits
7. Check for drug-drug and drug-allergy interactions
8. Record patient demographics
9. Maintain an up-to-date problem list of patients' current and active diagnoses
10. Maintain patients' active medication list
11. Maintain patients' active medication allergy list
12. Record and chart vital signs
13. Record smoking status for patients age 13+
14. Capability for electronic exchange of key clinical information among providers *
15. Protect electronic health information
Must Meet 5 Out of 10 Menu Objectives (Including at least Item 1 or Item 2)
1. Capability to submit electronic immunization data to public health databases
2. Capability to submit electronic disease surveillance data to public health databases
3. Generate disease registries (lists of patients with a specific condition – e.g., diabetes)
4. Send reminders to patients for preventive or follow-up care
5. Make patients' health information available to them electronically on a timely basis
6. Use EHR to provide patients with education resources specific to their conditions
7. Reconcile patient medications
8. Record a summary of care for each referral or other transition of care
9. Perform drug-formulary checks electronically
10. Store lab test results as structured data

* For 2014, the Stage 1 core requirements consist of only 13 items: reporting of clinical quality measures was moved to a separate category of requirements (and increased to 9 measures to be reported) while capability for exchanging clinical information among providers was dropped from Stage 1.

Source: Centers for Medicare and Medicaid Services, "Medicare & Medicaid EHR Incentive Program: Meaningful Use Stage 1 Requirements Overview," 2010, http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/MU_Stage1_ReqOverview.pdf, accessed September 14, 2013.

Table 17. Requirements for Physicians and Other Eligible Professionals for Meaningful Use Stage 2

Must Meet 17 Core Objectives
1. Use CPOE to order prescription drugs, lab tests, and imaging (radiology)
2. Electronic prescribing of pharmaceuticals
3. Record patient demographics
4. Record and chart vital signs
5. Record smoking status for patients age 13+
6. Use clinical decision support to improve performance on high-priority health conditions
7. Make electronic health information available for patients to download or transmit
8. Provide patients with clinical summaries of office visits
9. Protect electronic health information
10. Include lab test results in the EHR
11. Use disease registries (lists of patients with a condition) for quality improvement, reduction of disparities, research, or outreach
12. Use the EHR to identify patients due for reminders of preventive or follow-up care
13. Use the EHR to identify education resources specific to patient conditions
14. Reconcile patient medications
15. Provide an electronic summary of care for each referral or other transition
16. Submit electronic immunization data to public health databases
17. Communicate with patients by secure messaging
Must Meet 3 Out of 6 Menu Objectives
1. Submit electronic disease surveillance data to public health databases
2. Make notes in the patient's electronic record
3. Use the EHR to access imaging results
4. Document the patient's family medical history in the EHR
5. Identify patients with cancer and report them to a State cancer registry
6. Identify patients with a condition other than cancer and report them to a relevant registry

Source: Centers for Medicare and Medicaid Services, "Stage 2 Overview Tipsheet," August 2012, http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/Stage2Overview_Tipsheet.pdf, accessed September 14, 2013.

The regulatory standards in this area must walk a fine line. If the bar for meaningful use is set too high, many medical providers, especially physicians in smaller practices with fewer resources, may conclude they are unlikely to meet the incentive program requirements and therefore may not bother with even a less ambitious implementation of an EHR, or an initial adoption may stall at only a cursory level of usage. On the other hand, if the bar is set too low, EHR vendors may delay updating their products to include more ambitious capabilities or physicians and hospitals may take much longer to begin using some of the more important features of the EHR. In particular, how quickly and how much to expect physician and hospitals providers to exchange clinical data with other health care providers outside their own organization has emerged as one of the key issues for meaningful use standards, and interoperability in general has been recognized as a major challenge for the next phase of EHR adoption. For example, as an early test of interoperability, Meaningful Use Stage 1 originally included a requirement for physicians to demonstrate a capability to exchange electronic patient data with another, non-affiliated health care provider organization that uses a different EHR product, but in 2012 the final rule specifying the details of Stage 2 deleted this requirement from Stage 1 while specifying a more ambitious set of data exchange requirements for Stage 2. The interoperability issue under HITECH is discussed further below.

For professionals who achieved Stage 1 in 2011 or 2012 (the majority of existing program participants), these participants were originally supposed to achieve Stage 2 during calendar year 2014 (and federal fiscal year 2014 for hospitals). However, in contrast to the high participation rates achieved for Stage 1 (approximately 79% of eligible physicians and 94% of eligible hospitals receiving a Stage 1 payment), CMS data for through January 2015 indicate that only 7% of eligible professionals and 36% of eligible hospitals had met Stage 2 requirements in 2014 (Centers for Medicare and Medicaid Services 2015a). Many EHR vendors reportedly have been slow to provide software upgrades to make their systems fully compatible with Stage 2 requirements, fueling debate over whether the primary problem is lack of responsiveness among vendors or overly aggressive, complex regulations (Conn 2014a). In response to concerns voiced by physician and hospital stakeholders, in a rule published in September 2014 CMS provided flexibility on several aspects of Meaningful Use requirements applicable in 2014, including allowing those health care providers who were due to face Stage 2 requirements in 2014 to continue at Stage 1 instead (Centers for Medicare and Medicaid Services 2014). In the same rule CMS also delayed the start of the still-to-be-determined Stage 3 requirements from 2016 to 2017. Health care provider associations such as the American Medical Association (AMA) and the American Hospital Association (AHA) argued the changes were insufficient and continued to lobby for additional flexibility in the program (Tahir 2014; American Medical Association 2014). In January 2015 CMS announced that another regulation would be issued later in the year to provide additional flexibility for requirements in 2015 (Conway 2015).

A common theme in AMA and AHA comments as the Meaningful Use program has unfolded is that these stakeholders have supported the broad objectives and approach of the Meaningful Use program but have often argued that specific program requirements have been too aggressive for the many physicians and hospitals who have struggled to comply. Physicians and hospitals are in a difficult position with respect to meeting Meaningful Use standards because their ability to comply is often dependent on the capability and usability of their particular EHR system, so vendor performance in upgrading capabilities or providing customized support can be a key factor in how easily health care providers can earn the Meaningful Use incentives. Ongoing vendor performance can be a significant concern given that there are hundreds of vendors active in the physician EHR market, as discussed in the next section.

4.4 The competitive supply side of the EHR industry

In addition to influencing the behavior of potential adopters, regulatory decisions on what EHR capabilities and activities must be demonstrated for a physician or hospital to achieve each stage of meaningful use will also influence the supply side of health IT diffusion – i.e., EHR vendors. The HITECH financial incentives are tied to use of Certified EHR Technology (CEHRT), and ONC is responsible for administering the Certified HIT Product List (CHPL) (Charles et al. 2012). By late 2012, 795 vendors had a government-certified ambulatory (outpatient) EHR product (Gold et al. 2013, 355). Further, as of October 2012, 353 of these vendors had an EHR system that had been used by at least one professional to qualify for Meaningful Use incentive payments, while 107 vendors had an EHR used by at least one hospital to qualify for incentive payments (Gold et al. 2013, 356). As further evidence of the high level of competition, the largest market share for a single vendor accounted for approximately 20% of professionals who qualified for incentive payments, and 16 different firms collectively account for 75% of those professionals qualifying for incentive payments by October 2012 (Gold et al. 2013, 356). Even among very large physician practices (those with more than 50 physicians), over 100 different vendors had at least one customer who had qualified for incentive payments (Gold et al. 2013, 357). The Herfindahl-Hirschman Index for the outpatient EHR sector overall was 750, well below the 1,500-2,500 range that defines a "moderately concentrated" industry (Gold et al. 2013, 357; U.S. Department of Justice, Antitrust Division 2014). It is also worth noting that the EHR industry is diversified geographically, with approximately 20% of vendors headquartered in each of the northeast, midwest, and west regions of the U.S., 36% headquartered in the south, and 3% headquartered overseas (Charles et al. 2012, 3).

While ONC has generally touted this level of competition in the physician EHR market as a positive development because it implies a wide range of choice for adopters, physicians who have adopted smaller vendors' systems may be at significant risk in the event of an eventual market shakeout or if those small vendors cannot successfully upgrade their technology to keep pace with evolving regulatory requirements for Meaningful Use. Having hundreds of active vendors also makes interoperability even more of a challenge – an issue discussed in the next section.

4.5 Increased concern about interoperability

Concern about EHR interoperability and exchange of clinical health information gained new prominence in 2013 and 2014. In January 2013, two RAND researchers who were not associated with RAND's original 2005 EHR research published a commentary on the state of EHR adoption in which they lament that EHRs continue to suffer from poor usability and interoperability (Kellermann and Jones 2013). Kellermann and Jones (2013, 64) note that the EHRs "that currently dominate the market are not designed to talk to each other. . . . The lack of progress on interoperability is so stark that it has led some to speculate that major health IT vendors are opposed to interoperability."

In April 2013, six Republican senators issued a white paper criticizing multiple implementation issues in the Meaningful Use program, with "lack of a clear path to interoperability" being the first concern discussed (Alexander et al. 2013). The white paper also expressed concern about unintended cost impacts from EHR adoption, insufficient oversight of incentive payments, security of patient data, and long-term sustainability when adoption subsidies end. Despite this critique, however, to date the HITECH Act has not emerged as a recurring partisan issue, unlike the steady Republican criticism of the Affordable Care Act.

Concern about EHR interoperability continued to climb the policy agenda following an assessment by an independent panel of scientists from the federal government's JASON advisory group (JASON 2014). JASON is a long-standing stable of scientists whose members are available to conduct arms-length reviews of science and technology issues for federal agencies – usually in the national security sphere (Federation of American Scientists 2014). This JASON review was requested by HHS and was publicly released in 2014. The report's findings include, among others, the following four points:

1. "The current lack of interoperability among the data resources for EHRs is a major impediment to the effective exchange of health information" (JASON 2014, 3).

2. “The criteria for Stage 1 and Stage 2 Meaningful Use . . . fall short of achieving meaningful use in any practical sense” (JASON 2014, 6).
3. “Although current efforts to define standards for EHRs and to certify HIT systems are useful, they lack a unifying software architecture to support broad interoperability” (JASON 2014, 6).
4. “Current approaches for structuring EHRs and achieving interoperability have largely failed to open up new opportunities for entrepreneurship and innovation” (JASON 2014, 6).

As a result, the JASON report (2014, 7) recommended that ONC and CMS revise plans for Stage 3 of Meaningful Use to focus on “creation of an entrepreneurial space across the entire health data enterprise.” A key thrust of this shift would be for the Meaningful Use program to require EHR vendors to develop and make public Application Program Interfaces (APIs), akin to Apple and Android applications in the mobile phone and tablet market, that would allow third-party programmers to develop internet-based applications to “bridge from existing systems to a future software ecosystem” that would be “built on top of the stored data” (JASON 2014, 3). EHR vendors would also have to make data from their EHRs accessible to APIs developed by third parties (JASON 2014, 7).

To develop a proposed response to the JASON report, ONC’s health IT policy and standards committees formed a 22-member task force representing multiple stakeholders such as federal and state agencies, EHR vendors, health plans, and health care providers. This task force’s recommendations, presented in October 2014, endorsed certain points from the JASON report while rejecting others. The ONC task force agreed that interoperability should be based on public APIs and that Meaningful Use Stage 3 should be the pivot for this change in approach by focusing on interoperability, rather than continuing the Stage 1 and Stage 2 attempts to drive EHR usage across a wide range of capabilities (ONCHIT Interoperability and Health Information Exchange Workgroup 2014). However, the ONC task force also proposed that an API-based architecture should be market-driven and that "minimal, if any, federal regulatory intervention is desirable at the current stage of market development" (ONCHIT Interoperability and Health Information Exchange Workgroup 2014). The task force recommendations were unanimously approved by both of the parent policy and standards committees advising ONC (Conn 2014b). In December 2014, five major EHR vendors and four well-known healthcare providers announced a collaborative project to promote development of an initial set of public, standardized APIs (Conn 2014c).

It will be interesting to see whether the API approach gains real momentum. If so, it potentially could represent the type of technical discontinuity that generates an intensely competitive period of ferment as envisioned by Anderson and Tushman (1990), as discussed in Chapter 2. On the other hand, it also is possible that the major legacy EHR vendors may seek the appearance of enthusiasm for APIs while actually working to maintain their captive customer base. On balance, it seems likely that progress towards the open, API-based ecosystem envisioned in the JASON report will be gradual rather than sudden, at least in the near term.

4.6 Framing the policy context for assessing factors influencing adoption decisions

Thanks to the window of opportunity offered by the fiscal stimulus package, the HITECH Act of 2009 launched a major federal policy intervention intended to increase adoption of EHRs among U.S. physicians and hospitals. While there are multiple components of the HITECH Act, the ongoing Meaningful Use financial incentives program is its centerpiece, with incentive payments through December 2014 amounting to $10.7 billion for physicians and other professionals and $17.5 billion for hospitals, for a total of $28.1 billion through calendar year 2014. Yet as discussed in Chapter 2, financial barriers are only one of several factors that potentially influence physicians' decisions on whether to adopt an EHR, and Chapter 3 presented a quantitative methodology for testing a series of hypotheses regarding issues that may be significant to physicians' EHR adoption status. With the policy context presented above, particularly as underscored by the level of federal investment in the HITECH subsidies, we can now move, in Chapter 5, to the results of this quantitative analysis.

Chapter 5. Model Results And Follow-Up Analysis

As described in detail in Chapter 3, this dissertation examines 2011 and 2012 survey data to quantify and compare the extent to which different types of adoption issues reported by physicians predict their status as EHR adopters or non-adopters. Five composite scales representing different factors influencing adoption decisions were developed from more specific survey items, and the significance of these scales in predicting the dependent variable of adoption status can be tested with a set of logistic regression models. All five composite scales were tested in each model, but multiple model versions were specified because there are several issues that merit sensitivity testing. This chapter presents the results of these different models, including the variables of interest and an assessment of overall model performance. Because one of the key findings is that physicians' views on the HITECH financial incentives are an important predictor of adoption decisions since the launch of the incentives program, a follow-on section of the chapter presents more detailed analysis of physician participation in the incentives program.

Before presenting the model results, however, Table 18 provides a recap of the differences among the model specifications, which were justified in Chapter 3. Table 19 then presents the results of the six models.

Table 18. Matrix of Alternative Model Specifications

All models test the 5 composite scales reflecting physician-reported adoption facilitators/barriers; all models also include control variables for physician characteristics*				
Model	**Dependent Variable**	**Population**	**Observations (Physician Respondents)**	**Rationale**
Model Type 1: Cross-sectional data, logistic regression	Binary adoption status in 2011 (0= Not an EHR user, 1=EHR user)			Straightforward model and dependent variable definition of adoption
Model 1a. Base case population		Physician respondents in physician-owned practices of <=10 physicians	1,043	Larger sample size, respondents likely knowledgeable on adoption decision
Model 1b. Sens. test on population		Excluding those using an EHR before 2010	663	Focuses on adoption during HITECH period
Model 1c. Sens. test on population		Limit to physician-owned practices of 1-2 physicians	522	Very high confidence in respondents' knowledge on adoption decision
Model Type 2: Cross-sectional data, multinomial logistic regression	3 categories of 2011 adoption status (0=Not yet in process, 1=In process, 2=EHR user)**			More nuanced definition of adoption status for the dependent variable
Model 2a. Base case population		Same as 1a	1,043	Same as 1a, but more nuanced dependent variable
Model 2b. Sens. test on population		Same as 1b	663	Same as 1b, but more nuanced dependent variable
Model Type 3: Longitudinal data, logistic regression	Binary adoption status in 2012, given non-user status in 2011 (0=Not a user in 2012, 1=User in 2012)	2011 non-users who are also respondents in the 2012 survey, subject to the population criteria from model 1a	383	Longitudinal approach controls for unmeasured time-invariant respondent characteristics

* Control variables include: physician specialty (primary care, surgical, other), number of physicians in the practice, physician age, location in a metropolitan statistical area (MSA),U.S. Census region (northeast, south, midwest, west), and the number of NAMCS-eligible physicians in the state.
** "In process" defined here as the sum of: 1) those in the process of selecting an EHR system, plus 2) those who already purchased a system but were not yet using it.

Table 19. Model Results

	Model 1a	Model 1b	Model 1c	Model 2a		Model 2b		Model 3
Coding of dependent variable for EHR adoption status	0=Not an EHR user 2011, 1=EHR user 2011			0=Not yet in process 2011, 1=In process 2011, 2=EHR user 2011				0=Stayed a non-user 2012, 1=New user 2012
Composite scales for physician-reported importance of:	**Odds Ratio**	**Odds Ratio**	**Odds Ratio**	**Relative Risk Ratio**		**Relative Risk Ratio**		**Odds Ratio**
				1 (vs 0)	**2 (vs 0)**	**1 (vs 0)**	**2 (vs 0)**	
Improved information	0.165*** (0.046)	0.091*** (0.040)	0.177*** (0.081)	1.424 (0.521)	0.181*** (0.056)	1.456 (0.584)	0.102*** (0.048)	1.276 (0.698)
HITECH financial incentives	0.643 $^{+}$ (0.147)	2.327 $^{+}$ (1.104)	0.624 (0.230)	4.023*** (1.371)	0.968 (0.250)	5.726*** (2.340)	3.980 ** (2.004)	3.351 ** (1.524)
Product selection barriers	1.028 (0.258)	1.354 (0.489)	0.826 (0.321)	0.729 (0.277)	0.929 (0.248)	0.669 (0.244)	1.150 (0.426)	0.459 $^{+}$ (0.200)
Cost barriers	0.579 $^{+}$ (0.164)	0.260 ** (0.101)	0.607 (0.237)	0.610 (0.241)	0.502 * (0.162)	0.549 (0.209)	0.213*** (0.087)	1.359 (0.592)
Implementation barriers	0.564 $^{+}$ (0.184)	1.341 (0.818)	0.238 ** (0.128)	0.638 (0.251)	0.485 * (0.169)	0.636 (0.261)	1.210 (0.746)	1.264 (0.617)
Other independent variables								
Specialty (ref.=primary care)								
Surgical specialties	0.470 * (0.155)	0.469 (0.243)	0.269 * (0.140)	0.736 (0.352)	0.428 * (0.149)	0.789 (0.407)	0.471 (0.260)	1.057 (0.633)
Other specialties	0.415 ** (0.124)	0.578 (0.275)	0.176 ** (0.089)	1.150 (0.469)	0.417 ** (0.137)	1.347 (0.583)	0.650 (0.322)	1.335 (0.614)
Practice size (ref.=solo practice)								
2 physicians	5.382*** (2.178)	2.509 (1.908)	6.233*** (2.814)	1.631 (0.901)	5.462*** (2.158)	1.778 (1.015)	2.751 (2.056)	1.206 (0.893)
3-5 physicians	4.013*** (1.475)	1.256 (0.734)	Not Applic.	3.788 ** (1.725)	5.747*** (2.251)	3.960 ** (1.860)	1.943 (1.129)	1.774 (0.873)
6-10 physicians	4.356*** (1.803)	1.192 (0.847)	Not Applic.	6.834 ** (3.891)	7.846*** (3.645)	7.560 ** (4.436)	2.539 (1.877)	4.159 * (2.568)

Notes: $^{+}$ $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ Values in parentheses are standard errors.

Table 19. Model Results (Continued)

	Model 1a	Model 1b	Model 1c	Model 2a		Model 2b		Model 3
	Odds Ratio	Odds Ratio	Odds Ratio	Relative Risk Ratio		Relative Risk Ratio		Odds Ratio
				1 (vs 0)	2 (vs 0)	1 (vs 0)	2 (vs 0)	
Physician age (ref.=55-64)								
<35	2.051	2.602	0.565	0.154	1.201	0.440	1.889	0.175
	(2.104)	(3.082)	(1.178)	(0.194)	(1.059)	(0.514)	(2.072)	(0.235)
35-44	1.519	2.287	3.810 $^{+}$	1.297	1.748	1.144	2.478 $^{+}$	1.372
	(0.628)	(1.164)	(2.655)	(0.611)	(0.737)	(0.552)	(1.326)	(0.904)
45-54	1.566	2.151	4.183 **	1.006	1.636	0.841	2.025	0.869
	(0.484)	(1.141)	(1.866)	(0.457)	(0.582)	(0.397)	(1.135)	(0.392)
65+	0.390 *	0.123 *	0.255 *	0.684	0.358 *	0.654	0.102 **	0.476
	(0.162)	(0.102)	(0.160)	(0.391)	(0.162)	(0.384)	(0.088)	(0.298)
In an MSA	0.696	0.774	0.832	1.754	0.794	2.043	0.924	0.947
	(0.200)	(0.279)	(0.345)	(0.829)	(0.230)	(1.021)	(0.347)	(0.487)
Region (ref.=northeast)								
Midwest	1.038	2.149	1.828	1.503	1.120	1.557	2.505	1.452
	(0.384)	(1.503)	(1.183)	(0.632)	(0.486)	(0.681)	(1.842)	(0.787)
South	1.371	3.662 **	4.983 **	0.834	1.337	0.783	3.328 *	1.111
	(0.481)	(1.768)	(2.967)	(0.353)	(0.504)	(0.358)	(1.642)	(0.570)
West	1.409	2.204	3.121 $^{+}$	0.666	1.239	0.532	1.726	0.955
	(0.568)	(1.448)	(1.891)	(0.376)	(0.526)	(0.334)	(1.168)	(0.674)
No. of NAMCS-eligible physicians in the state (000s)	1.008	1.008	1.052 **	1.022	1.013	1.018	1.011	0.990
	(0.013)	(0.024)	(0.200)	(0.018)	(0.014)	(0.018)	(0.247)	(0.018)
Observations	**1,043**	**663**	**522**	**1,043**		**663**		**383**
McFadden's pseudo R^2	0.316	0.278	0.382	0.288		0.264		0.152
Efron's pseudo R^2	0.345	0.267	0.312	N/A		N/A		0.049

Notes: $^{+}$ $p < 0.10$ * $p < 0.05$ ** $p < 0.01$ *** $p < 0.001$ Values in parentheses are standard errors.

5.1 Interpretation of results

Before interpreting results for the individual variables of interest, some introductory comments on the models' goodness of fit are helpful. Although not as intuitive or useful as the traditional R^2 reported with ordinary least squares regression, pseudo R^2 results are sometimes reported for logistic regression models, although pseudo R^2 values should not be explicitly compared across models that, as in this case, differ with respect to the specification of the dependent variable and the observations included in each model (i.e., the full study population versus a portion of that population). While several versions of a pseudo R^2 are mentioned in the literature, McFadden's R^2 is a common version and the default in Stata version 13. As shown in Table 19, Models 1a, 1b, 1c, 2a, and 2b have McFadden's R^2 results that fall between 0.20 and 0.40 – a range that McFadden (1978, 307) describes as representing an "excellent fit." Model 3 falls below this range with a 0.15 result. A less common pseudo R^2 version recommended by Woolridge (2013, 591), the Efron's R^2 that reflects the square of the correlation between predicted and actual values for a binary logistic regression model, yields values that are similar to the McFadden's R^2 values for Models 1a, 1b, and 1c, but worse for Model 3; Efron's R^2 cannot be calculated for the multinomial models.

A more intuitive measure of fit for a logistic regression model is to generate predicted probabilities and then calculate the percent of predictions that are correctly classified – also known as the classification accuracy. However, the percent correctly predicted is a function not only of the model's goodness of fit but also the actual distribution of the underlying data into the different categories of the dependent variable.

For example, holding all else equal, there is a greater chance of an incorrect prediction when having to predict among three categories of the dependent variable (as in the multinomial logistic regression models 2a and 2b), compared with only two categories of the dependent variable (as in the standard logistic regression models 1a, 1b, 1c, and 3). As a result, a lower absolute percentage of correct predictions for a multinomial model compared to a standard logistic regression model would not necessarily indicate a poorer fit. Rather than directly comparing the percent correctly predicted across models that use different specifications of the dependent variable or different specifications of the data sample (i.e., different sub-populations), instead each model's classification accuracy should be compared to the percent of correct predictions that could result *by chance* for that given model's data and dependent variable specification.

A further nuance is that the literature on classification accuracy describes two alternative criteria for calculating the percent of predictions that could result by chance: the proportional chance criterion and the maximum chance criterion (Huberty 1984; Brown and Wicker 2000). The maximum chance criterion is the more conservative standard for assessing a model's classification accuracy because it reflects the highest accuracy percentage that could occur by chance. Further, the maximum chance criterion is more appropriate when the distribution of the actual observations in the underlying data is unbalanced between categories of the dependent variable, as in most of the models here (Huberty 1984, 170). For example, if 70% of the actual observations fell into one category of the dependent variable, then the maximum percentage of correct predictions that could result by chance is the 70% that would result if every observation were predicted to fall into that category.

Huberty (1984) also describes a formal significance test of classification accuracy (i.e., whether the percentage correctly predicted by the model is significantly different than what would be expected by chance). Table 20 below incorporates this significance test in presenting the predicted probability results for each of the six models. The percent correctly predicted is statistically significant at $p<0.001$ for Model's 1a, 1c, 2a, and 2b, while model 1b's classification accuracy is significant at $p<0.05$. Model 3's classification accuracy falls slightly short of the conventional 0.05 significance level, at $p<0.08$. Table 20 also indicates the magnitude of improvement above chance for each model's classification accuracy; the multinomial model 2a particularly stands out with a classification accuracy rate that is 53% higher than the maximum rate that would result by chance. All results in the table have also been adjusted to reflect the survey data's complex sampling design.

Table 20. Percent Correctly Predicted, Compared to By-Chance Accuracy

	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 3
Percent correctly predicted	75.9%***	88.8% *	83.5%***	66.0%***	69.3%***	80.6% $^{+}$
Maximum percent expected by chance	57.0%	86.3%	68.0%	43.0%	59.2%	77.6%
Ratio of percent correctly predicted to maximum percent expected by chance	1.33	1.03	1.23	1.53	1.17	1.04
N	1,043	663	522	1,043	663	383

Notes: $^{+}$ $p< 0.10$ * $p< 0.05$ ** $p< 0.01$ *** $p< 0.001$ Percent expected by chance reflects the Maximum Chance Criterion.

While overall model statistics such as the percent correctly predicted have value in assessing goodness of fit, a more important consideration is whether the model specification and results appear consistent with theory and common sense. This assessment is particularly important regarding the direction and magnitude of statistically significant effects for the variables of interest. Results that conflict with theoretical expectations may be reasonable but first merit further review to assess if the unexpected result is due to a flaw in methodology or data rather than a legitimate explanation or insight. This assessment is provided below.

In interpreting the results of these models, it is sometimes convenient to refer to the specific value of an odds ratio (for the standard logistic regression models) or a relative risk ratio (for the multinomial logistic regression models). However, a general caveat for the present analysis is that one should not place undue emphasis on the precise quantitative impacts reflected in these various results. The composite scale variables are limited in their precision, but as argued in Chapter 3, these explanatory variables do provide valuable comparative indicators of both direction and general magnitude of impact for the adoption factors in this study. Additional caveats are discussed in Chapter 6, but this introductory context paves the way for discussion of results for each of the five explanatory scales.

5.1.1 The influence of improved information

The models yield two results of interest with respect to the composite scale representing improved information. First, physicians who reported improved information as influential to EHR adoption had much lower odds of being an EHR adopter by 2011.

In Model 1a, a one-point increase on the three-point scale for information influences lowers the odds of being an adopter by 83% ($p<.001$). This result contrasts with the expectation, as expressed in hypothesis 1, that earlier adopters are more influenced by information factors than are later adopters or non-adopters. Further, this result is robust to sensitivity testing in model 1b that excludes those who adopted before 2010 and in model 1c that limits the population to physicians in solo or two-physician practices (who would be most knowledgeable about their practice's decision-making on EHR adoption). Very similar results are also found when EHR users are compared to those who were not yet even in the process of adoption in 2011, as tested in models 2a and 2b (although the results for these two models are reflected as relative risk ratios rather than odds ratios). Thus, while views on the importance of better information appear to be a predictor of adoption status as of 2011, those reporting improved information as influential were less likely to have adopted an EHR by 2011, not more likely.

Given the unexpected nature of this result, at least relative to hypothesis 1, further discussion is warranted. As described in Chapters 2 and 4, EHRs represent a particularly complex innovation and many physicians are uncertain about EHR usability and disruption of workflow, among other risks. Hypothesis 1 focused on the literature's finding that early adopters tend to be more integrated in networks and more active seekers of information, but Rogers (2003, 284) also observes that later adopters are cautious and need a significant reduction in uncertainty in order to "feel that it is safe to adopt." Mechanisms that reduce uncertainty for those who were not early or enthusiastic adopters would seem especially significant for complex innovations such as EHR adoption. Reviewing the information scale from this perspective, four of the five survey items in the scale seem well-aligned to mechanisms that reduce the uncertainties associated with adoption: government certification of products, assistance with EHR selection, assistance with implementation, and the legitimation role of "trusted colleagues." With this perspective, the unexpected result above appears more reasonable and the information scale as reflected in the models provides useful insight – just not the insight that was anticipated in the original hypothesis. The implications of this result are discussed in Chapter 6.

The second result of interest concerns the sub-group of physicians who in 2011 were on the verge of EHR adoption – those reporting that they were in the midst of adoption in 2011 (as isolated in the multinomial models 2a and 2b) or those newly becoming an EHR user in 2012 (as isolated in the longitudinal model 3).[9] Whether or not these physicians reported improved information as influential does not affect the odds of becoming a new EHR user in 2012. One possible explanation for this reduced importance of improved information in predicting which physicians remained non-adopters in 2012 and which became new users could be that the range of programs implemented under HITECH reduced any prior information gaps between adopters and non-adopters. This explanation could also include non-governmental information sources that may have expanded in response to HITECH (e.g., professional associations, consultants, and EHR vendors). Of course, it is also possible that improvements in information occurred simply by virtue of the continuing increase in EHR adoption over the past several years,

[9] There is substantial overlap in these two categories of new adopters, but the two models offer complementary approaches to analyzing these newest adopters.

independent of the HITECH Act. However, the argument for a HITECH impact is supported by also considering model 1b, which demonstrates that the physician's view on the importance of improved information was still a significant predictor of EHR adoption in the 2010-2011 period. Thus, the importance of information appears to have changed from the cohort of 2010-2011 adopters to the subsequent cohort who were only in the process of adoption as of 2011. This evidence is hardly definitive, however, and it is unfortunate that the subsequent rounds of the Physician Workflow Survey did not maintain the same set of questions in this area to allow a similar analysis of even more recent adopter cohorts.

5.1.2 The influence of the HITECH financial incentives program

While an overall impact assessment of the HITECH Meaningful Use incentives program is beyond the scope of this dissertation and would be premature at this stage of implementation, this research does yield interesting findings on the relationship between physicians' views on the incentives' influence and their own adoption status. In model 1a, the relationship between the HITECH financial incentives (the positive and negative incentives) and EHR adoption status is marginally significant ($p<0.06$), but the odds ratio indicates that physicians who report the incentives as influential to their adoption decision were less likely to be adopters. This counterintuitive result is explained by the fact that approximately 80% of the EHR adopters in the data for model 1a had adopted prior to the 2010 launch of the HITECH incentives program. Therefore, the HITECH incentives could not have been influential to these earlier adoption decisions.[10] On the other hand, there are non-users as of 2011 who reasonably report that their consideration of EHR adoption is influenced by the HITECH incentives even though they have not yet adopted. Clearly, model 1a is not a good fit for focusing on the HITECH incentives and the alternative specifications should be considered.

Model 1b provides one such alternative by excluding the pre-HITECH adopters. In this model, a one-point increase on the three-point scale for self-reported influence of the HITECH incentives increases the odds of being an adopter by 133% (marginally significant at $p<0.08$). Model 1c suffers from the same issue as model 1a, but models 2a and 2b offer another specification that focuses on adoption during the HITECH period by adding a third category to the dependent variable of adoption status -- to isolate physicians who were in the process of adoption in 2011. Being in the process of adoption is defined here as either in the midst of purchasing an EHR system or having purchased one but not yet using it. In model 2a, a one-point increase on the three-point scale for reported influence of the incentives increases the risk of being in the process of adoption in 2011 by 302% compared to the risk of not even being in the process of adopting ($p<.001$). In model 2b, which excludes pre-HITECH adopters, a one-point increase on the incentives scale increases the risk of being in the process of adoption in 2011 by 473% ($p<0.001$), and a one-point increase on the incentives scale also increases the risk of being a new user in 2010 or 2011 by 298% ($p<0.01$), compared to the risk of not even

[10] The HITECH incentives could certainly influence how these earlier adopters' will use their EHRs now or in the future, but that was not a focus of the "influence" questions in the survey, and this dissertation focuses on the initial adoption decision.

being in the process of adopting as of 2011. Finally, in model 3, a one-point increase on the incentives scale increases the odds of shifting from a non-user in 2011 to an EHR user in 2012 by 235% ($p<0.01$) compared to the odds of remaining a non-user in 2012. Thus, models 1b, 2a, 2b, and 3 are consistent in confirming hypothesis 2 -- that among physicians who were not already using an EHR before 2010, those who view the HITECH financial incentives as influential to their adoption calculus were much more likely to have become an adopter than physicians who do not view the incentives as influential.

These results for the influence of the HITECH incentives suggest there is value in further analysis of physician participation in the incentive program, and this follow-on analysis is provided later in this chapter.

5.1.3 The influence of product selection barriers

Hypothesis 3 predicts that physicians who reported difficulties in selecting a specific EHR product would be less likely to have adopted to date, given the literature on how network effects can inhibit adoption in the absence of interoperability or a dominant design. However, the composite scale for product selection barriers is not statistically significant at the conventional 0.05 level across any of the model results and only reaches even marginal significance ($p<0.10$) in model 3. Physicians may face issues in selecting a specific EHR vendor or system, but these issues do not appear to be a significant in predicting which physicians end up adopting and which do not. A key support for this finding is the fact, discussed in Chapter 4, that as of October 2012 over 350 different EHR vendors had sold systems to professionals who are participating in the Meaningful

Use incentives program (Gold et al. 2013, 356). Also, as of 2012 the Herfindahl-Hirschman Index for the outpatient EHR sector overall was 750, well below the 1,500-2,500 range that defines a "moderately concentrated" industry (Gold et al. 2013, 357; U.S. Department of Justice, Antitrust Division 2014). Despite literature cited in Chapter 2 that highlights physician concerns about product obsolescence, physicians to date have actually appeared quite willing to purchase their EHRs from an extremely wide range of suppliers. This physician willingness to purchase from such a wide range of vendors is also consistent with the finding in Models 2a, 2b, and 3 that there is not a significant difference in the influence of improved information between those who in 2011 were on the verge of becoming EHR users and those who were not yet even in the process of selecting an EHR.

5.1.4 The influence of cost barriers to adoption

The model results generally support hypothesis 4 that physicians who report cost as a greater barrier to EHR adoption are less likely to have adopted. In model 1a, which includes all adopters and non-adopters in physician-owned practices no larger than 10 physicians, a one-point increase on the three-point scale for cost barriers lowers the odds of being an adopter in 2011 by 42%, although this result is only marginally significant at $p<0.10$. When those adopting before 2010 are excluded, as in model 1b, a one-point increase on the cost barrier scale lowers the odds of being an adopter as of 2011 (meaning adoption in 2010 or 2011) by 74% ($p<0.001$). The multinomial logistic models 2a and 2b also estimate relative risk ratios of a roughly similar magnitude, although for those physicians in the process of adopting in 2011 the results are not statistically significant.

Model 3, on the other hand, finds that among physicians not using an EHR as of 2011, whether they report cost as a barrier to adoption does not have an impact on the likelihood of becoming a new EHR user in 2012 ($p=0.59$). However, this different finding for model 3 may largely be a function of model 3's poorer performance overall (as discussed above), with a smaller sample than any of the other models and only 84 observations switching from non-user to user status in 2012. The lack of impact for the cost variable in model 3 may also be due to the strong impact of the HITECH financial incentives.

5.1.5 The influence of implementation barriers

In the simplest model specification, model 1a which includes all EHR users and non-users as of 2011 in physician-owned practices no larger then 10 physicians, physicians who report various implementation issues as a barrier to adoption have lower odds of being an adopter, as expected under hypothesis 5. In this model a one-point increase on the three-point scale for implementation barriers lowers the odds of being an adopter as of 2011 by 44%, although at $p<0.08$ this result falls short of the conventional 0.05 significance level. The multinomial model 2a finds a very similar impact – a one-point increase on the implementation barriers scale lowers the relative risk of being an EHR user in 2011 by 51% ($p<0.05$). The impact of implementation barriers is even more pronounced when focusing on solo or two-physician practices (model 1c), for which a one-point increase on the implementation barriers scale lowers the odds of being an adopter as of 2011 by 76% ($p<0.01$). Finding a larger effect for implementation barriers among the smallest physician practices is logical and consistent with the literature, given they will tend to be more limited in IT expertise and related resources and, unlike larger practices, cannot phase their implementation with a few initial physicians.

When focusing on recent adoption decisions, however, physician concerns about implementation barriers no longer appear to be a significant predictor of adoption status. Models 1b, 2b, and 3 are consistent in finding that that the implementation barriers scale is not significant in predicting which physicians adopted in the 2010-2012 period. The implications of this finding are discussed in Chapter 6.

5.2 Overall model performance and cross-cutting comparison of the scales

As noted above, the accuracy rates for the predicted probabilities of all of the models except model 3 exceed the maximum that could occur by chance ($p<0.05$), while the percent correctly predicted for model 3 nears statistical significance at $p<0.08$. Model 2a (the multinomial logistic regression for the full study population) performs particularly well on this measure, with a 53% improvement relative to the maximum percent of correct predictions that could result by chance. All of the models except model 3 also have McFadden's pseudo R2 results falling within the 0.20 to 0.40 range, which McFadden (1978, 307) characterizes as representing an excellent fit for a logistic regression model. From a more general conceptual perspective, the multinomial specification of model type 2 is especially appealing because it allows for the possibility that those who are in the midst of adopting a complex innovation may differ both from those who have already adopted and from those who have not even decided to adopt. This nuance seems particularly useful when the data reflect a time period in the middle portion of the diffusion curve for a complex innovation, as in this case; i.e., a significant share of the population is in the process of adoption but there are also many existing adopters and many remaining non-adopters. As described above, the individual variable results in the multinomial models 2a and 2b also appear reasonable and hold together in suggesting a particularly good fit of the data.

Looking across the five variables of interest, physician views on the importance of improved information appear to have the largest impact among the different scales as a predictor of EHR adoption status as of 2011 when the full study population is included -- i.e., including those physicians who adopted prior to the HITECH period, as in Models 1a and 2a. As discussed above, physicians who reported improved information as important to their decision on whether to adopt an EHR were much less likely than other physicians to be an EHR user in 2011. However, the physician-reported importance of improved information was not significant as a predictor of which physicians were on the verge of becoming an EHR user in 2011 versus those who continued as non-adopters. For these most recent adoption decisions in the data, the HITECH financial incentives were by far the most significant variable. Given the approximately $11 billion in federal incentive payments to physicians as through December 2014 and the high level of policy interest in the impact of these incentives, further analysis of participation in the incentive program is worthwhile (Centers for Medicare and Medicaid Services 2015a).

5.3 Analysis of physician participation in the HITECH incentives program

The modeling results above find that the degree of importance physicians attach to the HITECH Meaningful Use financial incentives is the most significant predictor of EHR adoption decisions since the launch of the program in 2010 -- a result that merits further analysis of the Physician Workflow survey's data on participation in the incentive program. First, it is helpful to confirm that those physicians who reported the incentives program as influential to their adoption decision are actually planning to participate in the program. Table 21 below indicates that, among EHR adopters in small, physician-owned practices, 93% of those who reported the HITECH incentives or penalties as a major influence on their adoption decision either had already applied for Meaningful Use incentive payments as of 2012 or were planning to do so. This participation rate compares to 68% for other recent adopters who did not view the incentives as a major influence on their adoption decision, reflecting a statistically significant difference ($p<0.001$) and a 0.63 correlation.

Table 21. 2012 Status for Participation in the HITECH Incentives Program Among 2010-2012 EHR Adopters, Stratified by Reported Influence of the Incentives

	Reported the HITECH incentives as a major influence	Did not report the HITECH incentives as a major influence
Already applied or intend to apply	93%	68%
Will not apply or uncertain	7%	32%
Total	100%	100%

Notes: Difference in participation status is statistically significant ($p<0.001$) and the correlation between the incentives participation status and self-reporting the incentives as a major influence on the EHR adoption decision is 0.63.

Source: NCHS NAMCS Physician Workflow Supplement survey; data limited to physicians working in physician-owned practices no larger than 10 physicians who responded to the survey in both 2011 and 2012; reported influence of the incentives is as of 2011 because this question was not asked in the 2012 survey version; excludes survey responses completed by staff rather than a physician; N=217.

From a policy perspective it is also helpful to gauge the extent to which the incentive program is attracting participation from adopters who faced cost or productivity concerns with their adoption, since a key rationale for a subsidy in this context is to strengthen the business case for adoption. As shown in Table 22, among physicians in small, physician-owned practices who adopted their EHR since the launch of the incentive program, 91% of those who reported experiencing cost or productivity issues as a major barrier to adoption either had already applied for Meaningful Use incentive payments as of 2012 or were planning to do so. Thus, for later adopters whose cost:benefit ratio for adoption would benefit from the subsidy, over 90% of these physicians were planning to receive that benefit.

Table 22. 2012 Participation in the HITECH Incentives Among 2010-2012 EHR Adopters Who Reported a Cost/Productivity Issue as a Major Barrier to Adoption

Already applied or intend to apply	91%
Will not apply or uncertain	9%
Total	100%

Source: NCHS NAMCS Physician Workflow Supplement survey; data limited to physicians working in physician-owned practices no larger than 10 physicians who responded to the survey in both 2011and 2012; excludes survey responses completed by staff rather than a physician; N=193.

While Tables 21 and 22 examine participation rates among recent adopters who should be especially attracted to the HITECH incentives program, another useful perspective is to stratify those physicians who are participating in the program based on whether or not they appear to be appropriate targets for the incentives. Table 23 indicates that among 2012 program participants from the overall study population (those working in physician-owned practices no larger than 10 physicians, regardless of when they adopted their EHR), 80% reported experiencing a cost or productivity issue as a major barrier to adoption. Thus, a high percentage of program participants within the study population report experiencing an adoption barrier for which a subsidy would offer some relief.

Table 23. 2012 HITECH Incentive Program Participants Stratified by Whether They Reported a Cost/Productivity Issue as a Major Barrier to Adoption

Reported a cost/productivity issue as a major adoption barrier	80%
Did not report a cost/productivity issue as a major adoption barrier	20%
Total	100%

Source: NCHS NAMCS Physician Workflow Supplement survey; data limited to physicians working in physician-owned practices no larger than 10 physicians who responded to the survey in both 2011 and 2012; excludes survey responses completed by staff rather than a physician; N=273.

These tabulations support a finding that the HITECH incentives are attracting high rates of participation from those physicians whose business case for adoption would benefit from the subsidy. However, because the HITECH incentives are available regardless of when the EHR adoption took place, the program is also subsidizing many physicians whose decision to adopt an EHR was not influenced by the subsidies. Table 24 (below) indicates that among the program participants as of 2012 who worked in small physician-owned practices, almost half of these participants (47%) report that the incentives program was not a major influence on their adoption decision. Of course, as discussed in Chapter 4, simply inducing more threshold decisions to adopt an EHR is not the explicit goal of the incentives program in any case, a point made by one of the Congressional authors in explaining the program's rationale (Stark 2010). The incentives require not just acquiring an EHR but meaningful use, for which the regulatory definition is increasingly ambitious over each of the program's three stages. Therefore, even for the many current participants whose initial adoption decision was not influenced by the incentives, especially because they adopted before the launch of the incentives program, the incentives can still be influencing the ways in which these participants are now using their EHR. This broader impact is beyond the scope of this dissertation but certainly would be an essential component of a full program evaluation for the HITECH incentives.

Table 24. 2012 HITECH Incentive Program Participants Stratified by Whether They Reported the Incentives as a Major Influence on Their Adoption Decision

Reported the HITECH incentives/penalties as a major influence on the EHR adoption decision	53%
Did not report the HITECH incentives/penalties as a major influence on the EHR adoption decision	47%
Total	100%

Source: NCHS NAMCS Physician Workflow Supplement survey; data limited to physicians working in physician-owned practices no larger than 10 physicians who responded to the survey in both 2011 and 2012; reported influence of the incentives is as of 2011 because this question was not asked in the 2012 survey version; excludes survey responses completed by staff rather than a physician; N=252.

An additional caveat on this point is that Table 24 only presents a snapshot of program participants as of 2012. The share of participants who adopted since the launch of the incentives will continue to grow, and when focusing solely on these program participants, 79% report that the positive or negative incentives were a major influence on their adoption decision, as shown in Table 25.

Table 25. 2012 HITECH Incentive Participants Stratified by Whether They Reported the Incentives as a Major Influence on their Adoption Decision, Excluding Physicians Who Were Using an EHR Before 2010

Reported the HITECH incentives/penalties as a major influence on the EHR adoption decision	79%
Did not report the HITECH incentives/penalties as a major influence on the EHR adoption decision	21%
Total	100%

Source: NCHS NAMCS Physician Workflow Supplement survey; data limited to physicians working in physician-owned practices no larger than 10 physicians who responded to the survey in both 2011 and 2012; reported influence of the incentives is as of 2011 because this question was not asked in the 2012 survey version; excludes survey responses completed by staff rather than a physician; N=113.

To summarize, analysis of additional data in the survey specific to participation in the Meaningful Use program appears consistent with the modeling results that physician views on the positive and negative HITECH financial incentives are significant in predicting recent EHR adoption decisions among physicians in small physician-owned practices. Within this population, over 90% of adopters who reported the incentive payments or penalties as a major influence on their adoption decision were participating in the Meaningful Use program as of 2012 or were planning to do so, and over 90% of the recent adopters who faced a cost or productivity issue as a major barrier to adoption were participating in the program as of 2012 or were planning to do so.

Given the modeling results for all of the explanatory variables and this follow-on analysis of participation in the HITECH incentives program, the remaining task for this study is to discuss the implications and limitations of these findings. Chapter 6 provides this discussion.

Chapter 6. Conclusions, Limitations, And Implications

This final chapter begins with conclusions drawn from the results of the analysis, followed by a discussion of key limitations. Final sections discuss implications for policy and for future research.

6.1 Conclusions

The results in Chapter 5 suggest several conclusions with respect to EHR adoption in the population of interest in this study – U.S. physicians in physician-owned practices of no more than 10 physicians. First, multiple models that isolate recent adopters in the Physician Workflow survey data find that physician views on the importance of the HITECH financial incentives were a strong predictor of adoption status. Consistent with this finding and with the health IT literature, the model results also generally confirm that cost has been a barrier to adoption. These modeling results are also supported by follow-on analysis of the survey data related to participation in the incentives program. Among physicians in small physician-owned practices, an estimated 80% of 2012 participants in the HITECH incentives program reported experiencing a cost or productivity issue as a major barrier to adoption, and over 90% of physicians who became EHR users in 2010 or 2011 (the early HITECH period) and who reported a cost or productivity issue as a major barrier to adoption were either participating in the incentives program by 2012 or were planning to do so.

Two more findings concern the role of information in EHR adoption among the study population. The value physicians attach to improved information, as reflected in the available survey items comprising that composite scale, is a significant predictor of which physicians in the study population were using an EHR by 2011, but not in the direction that was expected. Based on findings in the literature that early adopters tend to be more integrated in networks and more active seekers of information, one hypothesis for this study had been that better information would matter more to early adopters, but the model results consistently indicate that those physicians reporting improved information as influential to adoption were less likely to have adopted by 2011, not more likely. This finding holds even when those who adopted before 2010 are excluded; i.e., reporting improved information as influential to an EHR adoption decision greatly decreases the likelihood of being a new EHR user as of 2010 or 2011, compared to the likelihood of being a non-user.

There is a reasonable explanation for this finding, however. As discussed in Chapter 5, the literature also suggests that later adopters are cautious and need a significant reduction in uncertainty before adopting a complex innovation such as an EHR, so mechanisms that reduce uncertainty would be important for later adopters. Similarly, if some late adopters are experiencing information overload due to the complexity of an EHR adoption decision, mechanisms which help to cut through that complexity would also be important to their decision-making. Reviewing the information scale from this perspective, four of the five survey items included in the information scale are well-aligned to such mechanisms for reducing uncertainty or complexity, and in this context it is reasonable to conclude that information needs were less important to an EHR adoption decision for early adopters than for later adopters or non-adopters. Of course, it is possible that this finding could simply reflect measurement error, if the passage of time might cause those who have already adopted to downplay how important information was in an earlier decision. However, I discount this alternative explanation given that 2011 respondents who became EHR users as recently as 2010 or 2011 have approximately the same result for the information variable as those who adopted many years earlier.

A related finding is that the same composite scale for improved information is no longer significant when attempting to predict which physicians were in the midst of EHR adoption in 2011 (in the midst of purchasing or installing a system) and which were not even to that point. Given that the impact of the information scale was very significant when comparing non-users to those who became users in 2010 or 2011, it is interesting that this impact is no longer present when shifting the comparison to the next cohort of adopters (those in-process as of 2011). One possible explanation for this finding is that the range of programs implemented under the HITECH Act, perhaps in combination with non-governmental sources of information that expanded in response to HITECH (e.g., expertise from professional associations, EHR vendors, and private consultants), may have sufficiently leveled the playing field by 2011 such that a need for better information is no longer a discriminator between the newest adopters and those who continue to be non-adopters. The evidence for such a conclusion is hardly definitive, however.

This research also yields a surprising finding regarding adoption behavior for a network technology. As discussed in Chapter 2, the literature on network technologies predicts a low adoption rate until potential adopters have confidence about interoperability, which typically results from promulgation of sufficient technical standards or emergence of a dominant design. In the case of EHR adoption among U.S. physicians, the technology is widely viewed as still lacking meaningful interoperability, as described in Chapter 4. Yet multiple pieces of evidence indicate adoption behavior that differs from what the literature would predict:

- First, the data presented in Chapter 1 demonstrate that even before the effects of the HITECH financial incentives and related HITECH policies, adoption had almost reached a majority of potential adopters, with 48% of physicians using some type of EHR by 2009 (the year Congress passed the HITECH Act), and this adoption rate had reached 78% by 2013 – albeit now including HITECH effects (Hsiao and Hing 2014).
- Second, despite the lack of interoperability, thus far physician adopters have not gravitated to a dominant vendor. As discussed in Chapter 4, the physician EHR market has a very low level of concentration. As of October 2012, physicians collectively had purchased EHRs from over 350 different vendors; the largest market share for a single vendor accounted for approximately 20% of professionals who qualified for HITECH incentive payments; and 16 different vendors collectively accounted for 75% of those professionals who had qualified for incentive payments (Gold et al. 2013).

- Third, the quantitative models presented in this study consistently indicate that concerns about selecting a specific EHR vendor or system are not significant in predicting which physicians have adopted an EHR to date and which have not.

Based on this set of evidence, it is fair to conclude that physician behavior in adopting EHRs has not matched what would be expected given the literature on network technologies or given the prominence of physician concerns about the risk of product obsolescence in earlier health IT literature cited in Chapter 2. Possible explanations for this finding are provided below in the discussion of implications for future research.

A final conclusion addresses the significance of operational implementation barriers to EHR adoption. As described in Chapter 5, the model results indicated mixed impacts for the influence of implementation barriers. As expected, physicians who reported implementation barriers as influential to their adoption decision were less likely to have adopted an EHR by 2011. Further, the impact of physician concerns about implementation barriers was largest among practices with only one or two physicians, which is logical and consistent with existing literature, given that these practices will tend to be more limited in IT expertise and related resources and also do not have the option of phasing in their implementation with a few initial physicians. However, when focusing specifically on adoption decisions after 2009 (during the HITECH period), physician views on the influence of implementation barriers are no longer significant in predicting which physicians became new adopters and which continued to be non-adopters. While more a theory than a firm conclusion, a reasonable reconciliation of these pre- and post-HITECH findings would be as follows. EHR adoption decisions prior to the HITECH Act were made without the impact of the externally-imposed HITECH incentives, and therefore, holding all else equal, those physicians with major concerns about operational implementation issues would logically be less likely to adopt in this period than those who did not have major concerns about implementation. For adoption decisions in the 2010-2012 period, however, the HITECH incentives program appears to be the key factor influencing adopters, as discussed above, and thus this newly introduced impact appears sufficient to overcome implementation concerns among this cohort of adopters, who are neither early nor very late adopters.

6.2 Caveats to the analysis

In considering these findings, there are several limitations to acknowledge. First, the composite scales serving as explanatory variables are imperfect measures of the underlying adoption factors they represent, and as previously noted there is a false precision in the specific odds ratios and relative risk ratios resulting from the respective models. However, as described in detail in Chapter 3, the development of these scales follows recommended practice including an explicit quantitative justification relying on both factor analysis and acceptable values for Cronbach's alpha (the widely used index of reliability for a composite scale of survey items), as well as good face validity. As a result, although blunt, the explanatory scales appear to provide reasonable comparative indicators of both direction and general magnitude of impact for the adoption factors in this study.

A second measurement issue in this analysis concerns a problem more typically associated with an establishment survey – that the person actually responding on behalf of the sampled organization may not have sufficient institutional knowledge to provide accurate responses to some questions. The Physician Workflow survey is not technically an establishment survey because the survey's formal unit of analysis is individual physicians rather than physician practices, but the data still share this measurement risk. The relevant survey questions asking whether various issues were influential to the EHR adoption decision concern a decision that was likely made for the physician practice as a whole. In a formal establishment survey, the issue of institutional knowledge might sometimes be mitigated by a conscious effort to identify an appropriate individual within the sampled organization who is knowledgeable enough to respond accurately on behalf of the organization or who can coordinate internal gathering of information needed for an accurate response. In the Physician Workflow survey, however, the individual physicians included in the overall survey sample were not selected by the survey administrators based on any special knowledge of their organizations, such as the practice's decision-making on EHRs. Therefore, to mitigate this measurement issue for the present research, the methodology described in Chapter 3 includes two data filters:

- The analysis excludes physicians working in practices larger than 10 physicians and practices owned by larger organizations (hospitals, HMOs, etc.), since for these practices there is a high risk that decision-making on EHR adoption would have occurred at a level distant from the specific physician responding to the survey.[11]

[11] In the data provided by NCHS, the variable for practice size is categorical rather than continuous and the largest of the five size categories is "greater than 10."

- The analysis also excludes those survey responses where an administrative staff member completed the survey rather than the sampled physician. Most of these responses from administrative staff were collected by phone interview rather than the survey's normal mail mode, and therefore it is unlikely these staff respondents would have had sufficient time to consult with the sampled physician, or even any physician. Staff responses are also excluded simply for internal consistency – to ensure that the data represent the views of physicians rather than support staff.

As a third caveat, while this analysis provides insight on multiple issues of interest in the health IT literature and the broader diffusion literature, the analysis does not address all the factors that might be relevant to physician decisions on EHR adoption. For example, Chapter 2 notes that the epidemic model is a frequent focus in the diffusion literature, but the present analysis does not include a pure test of the epidemic model. One method for testing the epidemic model of diffusion is to collect and analyze detailed qualitative data mapping each adopter's specific network relationships and contacts with other adopters, as in the study by Coleman et al. of physician adoption of tetracycline in the 1950's, as described in Chapter 2. However, this approach would require direct access to the subjects in the study for intensive, follow-up data collection, and for the present research such direct follow-up contact by the author is prohibited by NCHS's survey confidentiality policies.

Absent such qualitative data on interpersonal contacts among adopters, in some cases survey data can be used for a geospatial analysis consistent with an epidemic model, but in the present case such an analysis was not feasible due to NCHS's de-identification of the state variable in the survey data available to the author (again due to confidentiality policies). A model version was tested on a preliminary basis using the de-identified state variable as a categorical dummy variable, but performance was quite poor due to small sample sizes for many states. As an alternative, however, the regression models used in the study do include several variables that relate to geography and the epidemic model, including the physician's U.S. Census region (the only level of identifiable geographic area in the data NCHS provided to the author), whether or not the physician is located in an MSA (an indication, albeit imperfect, of geographic proximity to other physicians), and a continuous variable for the number of physicians in the state (again, an imperfect measure for the degree of exposure to other physicians). In joint tests of significance, the region variable was significant at $p<0.05$ only in model 1c (with a smaller sample size of 522, due to limiting the population to solo and two-physician practices), while region was marginally significant ($p<0.10$) in models 1b and 2b (both of which exclude pre-2010 adopters). In all three cases, physicians in the South were more likely to be EHR adopters than physicians in the Northeast (the reference region); none of the models showed a significant difference in adoption status for physicians in the Midwest or West relative to physicians in the Northeast. MSA status was not significant in any of the models, and the number of physicians in the state was only significant in one of the six models (model 1c, in which the odds of EHR adoption increase as the number of physicians in the state increase).[12]

[12] Despite the lack of statistical significance for the MSA variable and the youngest physician age categories, likelihood ratio tests for the impact of removing the MSA variable from the models or collapsing the youngest physician age categories indicated statistically significant improvements in fit by

As a final caveat, while the findings regarding both the HITECH incentives program and the interoperability issue have important policy implications as discussed below, this research does not address all of HITECH's potential impacts on physician's usage of EHRs. The incentives program will continue to operate for several more years, and in addition to spurring threshold decisions to adopt, as analyzed in this study, the Meaningful Use program is also intended to increase the scope and intensity of EHR usage once adopted, including for those who adopted prior to the incentives program.

6.3 Policy implications

The conclusion that the HITECH financial incentives program is an influential factor in recent physician EHR adoption decisions is an important finding for the early experience of the program. This is hardly sufficient to predict success for the incentives program, however, given that HITECH objectives also include increasing the intensity and scope of EHR usage, rather than simply acquisition of the technology. Further, the ultimate impact of the HITECH incentives will depend in part on a longer term judgement of whether acceleration of adoption due to government-imposed financial incentives ultimately stimulated beneficial technological progress or premature lock-in of inferior designs. Nonetheless, in the short term, increasing the number of EHR users is a necessary first step towards HITECH's broader objectives, and this finding suggests the incentives program is contributing to that necessary first step.

---

keeping these variables in the models. The same is true for the variable reflecting the number of physicians in the state, which was only significant in model 1c.

Beyond direct implications for the HITECH Act, this impact of government-imposed financial incentives also has broader implications for many health system reforms anticipated in the 2010 Patient Protection and Affordable Care Act (PPACA, or commonly the ACA). As discussed previously, EHRs represent a complex innovation with a weak business case from the perspective of the adopting physician, given the traditional incentives in the U.S. health care system. Therefore, the finding that government-imposed financial incentives are influencing physicians to adopt this type of complex innovation despite multiple potential barriers suggests that it will also be important for other complex health delivery reforms to include an explicit financial incentives component when the business case for adoption is questionable from the physician's perspective. For example, many health plans, including the federal Medicare program, are currently testing the patient-centered medical home (PCMH) model for primary care physicians, in which a physician practice implements an ambitious range of transformations to improve the quality and efficiency of care provided to patients who rely on that practice for their primary care (their "medical home"). Examples of these transformations include expanding office hours to evenings and weekends, hiring additional nursing staff to track and coordinate care for complex patients (especially care delivered by other organizations such as specialists and hospitals), implementing web portals to communicate with patients by secure electronic messaging, and measuring physician performance on a wide range of metrics.

Such practice changes require investments of money and time, but insurers' traditional fee schedules for physicians typically do not cover most of these new activities. Most PCMH initiatives include some degree of financial incentive component, but there is significant variation in the magnitude and type of incentive provided. Some PCMH initiatives explicitly include a special payment to participating physicians, often as a monthly payment per patient who relies on that physician (or practice) for primary care (E. F. Taylor et al. 2015; Kahn et al. 2015). Sometimes this monthly payment is quite modest; in other cases it can be a significant revenue source for the participating physicians. Some initiatives offer participating physician practices an opportunity to share in overall health care utilization savings that may result from implementing the PCMH model, but there is uncertainty whether such savings will actually occur (E. F. Taylor et al. 2015). Given that transforming a primary care practice is complex and involves significant costs that typically are not reimbursed by existing revenue streams, much like EHR adoption, this present study's findings suggest that including explicit, meaningful financial incentives in a PCMH initiative will be important to attracting widespread participation, especially when moving beyond early adopters to scale up adoption by the broader population.

A second conclusion above that has implications for efforts to promote diffusion of health delivery reforms like the PCMH model is the finding that improved information, which reduces uncertainties regarding adoption, may be more important to later adopters than early adopters. This is important because the Centers for Medicare and Medicaid Services (CMS) has included a range of technical assistance components in several of its initial demonstrations testing the impacts of physician adoption of the PCMH model. Examples of the types of information provided through such programs includes training of physicians and their staffs, opportunities to network and discuss implementation issues with other demonstration participants, and sharing of performance reports and other data (E. F. Taylor et al. 2015; Kahn et al. 2015). Once these ongoing demonstrations are evaluated, it will be interesting to see whether the participating physicians viewed the information provided in these technical assistance programs as valuable. However, the research herein suggests that even if it turns out that the early adopters volunteering for these demonstrations did not view government-sponsored technical assistance as particularly helpful, such programs may have greater value in attracting and supporting the broader population of physicians who are more reluctant to adopt.

There are also important policy implications to the finding above that the physician EHR market has failed to converge on a dominant design. Many of the theorized benefits from EHR adoption require interoperability, to allow easy electronic exchange and aggregation of patients' health information. Given that a majority of physicians have now adopted EHRs which currently lack meaningful interoperability, and they have collectively purchased these systems from many different vendors, achieving the intended EHR benefits involving health information exchange will be more difficult, and more aggressive federal policies are needed to push progress towards interoperability. As discussed in Chapter 4, the recent JASON panel report on EHRs recommended policies supporting an internet-based ecosystem in which Application Program Interfaces (APIs) would make EHR data from legacy systems accessible through a range of creative third-party software products, as has occurred in the mobile phone market. The policy and standards committees advising ONC endorsed a pivot towards APIs as an architecture for interoperability, but these multi-stakeholder committees urged a market-driven strategy with minimal regulatory involvement for now. In March 2015 CMS (2015b) proposed a rule for the next stage of the Meaningful Use incentive program (Stage 3) that would include the API concept as an option for how physicians could satisfy a requirement to give patients access to their EHR data, and a parallel proposed rule from ONC (2015) would update certification of EHRs to include this API capability. Physicians would not have to reach Stage 3 until 2018, however, and it seems unlikely these proposed provisions will provide a sufficient incentive for many EHR vendors to invest seriously in a new business model focused on widespread support of APIs or major progress on interoperability more generally.

6.4 Implications for further research

The finding that physician adopters have not behaved as the literature on network technologies would predict also suggests several questions meriting future research, both to refine HITECH implementation and for interest in the scholarly literature on diffusion. First, one possible explanation for why physicians have not behaved as the network technology literature would expect is that perhaps physicians do not actually view EHRs as having the attributes that define a network technology. Do physicians actually perceive that their EHR is more valuable as adoption and interoperability increase? How much do physicians actually value an electronic capability to exchange digital patient data with other organizations (other medical providers, health plans, researchers, etc.)? For example, easy electronic exchange of patient data has obvious value for patients who often see multiple medical providers, and at a systemic level improved care coordination and elimination of redundant tests could yield cost savings and better outcomes, but individual physicians or practices may not perceive as much direct benefit from such data exchange (at least in the traditional fee-for-service physician payment environment). In the Physician Workflow survey data, as of 2011 only 23% of EHR adopters in the study population (physicians in physician-owned practices of no more than 10 physicians) reported that a capability for electronic exchange of patient information was a major influence on their decision to adopt. However, it is not clear if this statistic means that many physicians do not place a high priority on exchange of patient data in general, or if it simply means that many adopters to date viewed this capability as a longer term issue that was not an immediate concern at the time of adoption. Current rhetoric from many organizations representing physicians certainly stresses the need for improving health data exchange. For example, a joint letter from 35 physician organizations to ONC in January 2015 called for improvements in ONC's implementation guidance related to current health data exchange standards and more realistic testing of an EHR's capabilities for health data exchange as part of the government-sponsored certification of EHR products (American Medical Association et al. 2015).

Thus, an alternative explanation to investigate is whether physician behavior in selecting such a wide range of vendors and products to date has reflected poor information – i.e., at the time of purchase, have many physicians simply misunderstood the degree of interoperability in the EHRs they were selecting? For example, did many physicians assume that government-sponsored certification meant that the EHR would be capable of meaningful, easy data exchange? Or, as a third possible explanation to investigate, did adopting physicians correctly understand the low level of interoperability in current EHR technology but with an assumption that the problem would somehow be resolved soon on an industry-wide basis, such that existing, installed products could be made interoperable through a normal upgrade process? Answering such questions through further research would help refine current HITECH policies regarding certification of EHRs and education for would-be adopters. These answers would also be of interest to diffusion scholars, to explain why EHRs have now diffused widely despite the lack of interoperability or a dominant vendor or design.

This study also offers a methodological implication for future diffusion research. Many studies of diffusion tend to take a binary perspective comparing adopters to non-adopters, especially for quantitative analysis. However, in the case of complex innovations which likely involve an extended time period to implement adoption, a more useful approach, or at least an important complementary approach, is to use a more nuanced definition of adoption status that distinguishes those in the process of adoption from those who have already adopted and those who have not yet even begun the adoption process (as in models 2a and 2b in the present research). Recognizing “in-process” as a distinct adoption status would also seem more relevant when the research is conducted while near the middle of the diffusion curve, when a significant share of the population may be in the process of adoption.

Finally, given these findings about adoption facilitators and barriers for U.S. physicians, it would be useful to explore EHR diffusion in other advanced national health systems to determine if similar factors were present and how different national approaches to EHR diffusion have addressed such factors. The HITECH Act represents one national government's approach to promoting EHR diffusion, but this combination of information provision and financial incentives is not the only possible national strategy for diffusion of health IT. Studies by Jha and Blumenthal (2008) and Castro (2009) both serve as valuable early contributions in comparative international analysis of health IT adoption, but there have been numerous developments since then for national health IT initiatives and broader national health reforms. For example, despite already realizing a high level of EHR usage among primary care physicians, England's National Health Service tried a centralized procurement of a single EHR system that would be disseminated to all medical providers nation-wide to facilitate electronic exchange of patient data (especially involving hospitals). However, after multiple design issues, delays, and cost increases, in 2011 the government canceled the project as an expensive failure (Campbell 2011).

To conduct this type of cross-national analysis of health IT diffusion, it is important to have valid quantitative data on the level and scope of EHR usage. While several national health systems among the OECD countries appear to have achieved very high rates of EHR adoption for physicians, currently available cross-national comparisons can be quite sensitive to definitions of EHR usage. For example, in a widely cited Commonwealth Fund survey of primary care physicians in 10 countries, Norway ranked among the highest adoption rates with 98% of primary care physicians using any type of EHR, but when the study focused on use of a "multifunctional" EHR (defined as using at least two of four specific capabilities assessed in the survey), Norway ranked lowest of the 10 countries with only a 4% usage rate (Schoen et al. 2012). On the other hand, England, New Zealand, and Australia ranked high on both measures in this particular survey, with over 90% of primary care physicians using any type of EHR and a majority using a multifunctional EHR (Schoen et al. 2012). In recognition of such data issues, the 2013 edition of the Robert Wood Johnson Foundation's annual report on health IT includes a status update on several emerging sources of cross-national data on EHR adoption, including an important new OECD initiative to develop and collect standardized benchmark measures for national rates of health IT diffusion (Adler-Milstein, Winn, and Jha 2013). Once these new OECD data are available, ideally it should be possible to combine these health IT measures with existing OECD health system data to conduct a more systematic assessment of how other advanced national health systems are faring with IT adoption and whether any policies or other factors at the national level seem to be associated with higher or lower national rates of EHR adoption. With rising interest in possible mid-course adjustments for HITECH policies in the United States, availability of this quantitative data from the OECD would provide a valuable opportunity to learn from other nations' experiences with EHR diffusion.

In the meantime, however, the findings in this present study and the suggestions for further research should provide useful insights for evaluating and refining current U.S. policies for diffusion of health IT and other complex health care delivery innovations.

References

Abelson, Reed, and Julie Creswell. 2012. "U.S. Warns Hospitals on Medicare Billing." *The New York Times*, September 24. http://www.nytimes.com/2012/09/25/business/us-warns-hospitals-on-medicare-billing.html.

Abelson, Reed, Julie Creswell, and Griff Palmer. 2012. "Medicare Bills Rise as Records Turn Electronic." *The New York Times*, September 21. http://www.nytimes.com/2012/09/22/business/medicare-billing-rises-at-hospitals-with-electronic-records.html?pagewanted=all&_r=0.

Adler-Milstein, Julia, Carol E. Green, and David W. Bates. 2013. "A Survey Analysis Suggests That Electronic Health Records Will Yield Revenue Gains for Some Practices and Losses for Many." *Health Affairs* 32 (3): 562–69.

Adler-Milstein, Julia, Laura Winn, and Ashish K. Jha. 2013. "International Comparisons: Benchmarking HIT Adoption and Cross-Country Learning." In *Health Information Technology in the United States: Better Information Systems for Better Care, 2013*, edited by Catherine M. DesRoches, Michael W. Painter, and Ashish K. Jha, 34–43. Princeton, NJ: Robert Wood Johnson Foundation.

Alexander, Lamar, Richard Burr, Tom Coburn, Mike Enzi, Pat Roberts, and John Thune. 2013. "REBOOT: Re-Examining the Strategies Needed to Successfully Adopt Health IT." http://www.thune.senate.gov/public/index.cfm/files/serve?File_id=0cf0490e-76af-4934-b534-83f5613c7370.

American Medical Association. 2014. "AMA Provides Blueprint to Improve the Meaningful Use Program." October 14. http://www.ama-assn.org/ama/pub/news/news/2014/2014-10-14-ama-blueprint-improve-meaningful-use.page.

American Medical Association et al. 2015. "Joint Letter to Dr. Karen DeSalvo, National Coordinator for Health Information Technology," January 21. http://www.aafp.org/dam/AAFP/documents/advocacy/health_it/emr/LT-ONC-EHRCertification-012115.pdf.

Anderson, Andy B., Alexander Basilevsky, and Derek P. J. Hum. 1983. “Measurement: Theory and Techniques.” In *Handbook of Survey Research*, edited by Peter H. Rossi, James D. Wright, and Andy B. Anderson, 231–87. San Diego, CA: Academic Press.

Anderson, Philip, and Michael L. Tushman. 1990. “Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change.” *Administrative Science Quarterly* 35 (4): 604–33.

Angst, Corey M., Ritu Agarwal, V. Sambamurthy, and Ken Kelley. 2010. “Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals.” *Management Science* 56 (8): 1219–41.

Arthur, W. Brian. 1989. “Competing Technologies, Increasing Returns, and Lock-In by Historical Events.” *The Economic Journal* 99 (394): 116–41.

———. 1996. “Increasing Returns and the New World of Business.” *Harvard Business Review* 74 (4): 100–109.

Asch, Steven M., Elizabeth A. McGlynn, Mary M. Hogan, Rodney A. Hayward, Paul Shekelle, Lisa Rubenstein, Joan Keesey, John Adams, and Eve A. Kerr. 2004. “Comparison of Quality of Care for Patients in the Veterans Health Administration and Patients in a National Sample.” *Annals of Internal Medicine* 141 (12): 938–45.

Biemer, Paul P. 2010. “Total Survey Error: Design, Implementation, and Evaluation.” *Public Opinion Quarterly* 74 (5): 817–48.

Bigelow, James H., Kateryna Fonkych, Constance Fung, and Jason Wang. 2005. “Analysis of Healthcare Interventions That Change Patient Trajectories.” Santa Monica, CA: RAND Corporation.

Blavin, Fredric, Christal Ramos, Arnav Shah, and Kelly Devers. 2013. “Lessons from the Literature on Electronic Health Record Implementation.” Washington DC: Urban Institute. http://healthit.gov/sites/default/files/hit_lessons_learned_lit_review_final_08-01-2013.pdf.

Blumenthal, David. 2011. “Wiring the Health System -- Origins and Provisions of a New Federal Program.” *The New England Journal of Medicine* 365 (24): 2323–29.

Blumenthal, David, Catherine DesRoches, Karen Donelan, Timothy Ferris, Ashish Jha, Rainu Kaushal, Sowmya Rao, Sara Rosenbaum, and Alexandra Shield. 2006. “Health Information Technology in the United States: The Information Base for Progress.” Princeton, NJ: The Robert Wood Johnson Foundation.

Brown, Michael T., and Lori R. Wicker. 2000. "Discriminant Analysis." In *Handbook of Applied Multivariate Statistics and Mathematical Modeling*, edited by Howard E. A. Tinsley and Steven D. Brown. San Diego, CA: Academic Press.

Buntin, Melinda Beeuwkes, Matthew F. Burke, Michael C. Hoaglin, and David Blumenthal. 2011. "The Benefits of Health Information Technology: A Review of the Recent Literature Shows Predominantly Positive Results." *Health Affairs* 30 (3): 464–71.

Burt, Ronald S. 1987. "Social Contagion and Innovation: Cohesion Versus Structural Equivalence." *American Journal of Sociology* 92 (6): 1287–1335.

Bush, George W. 2004. "Remarks to the American Association of Community Colleges Convention." Minneapolis, MN, April 26. http://www.gpo.gov/fdsys/pkg/PPP-2004-book1/pdf/PPP-2004-book1-doc-pg667-2.pdf.

Cai, Bill, and Iris Shimizu. 2012. "Electronic Medical Record Systems Nonresponse Bias Analysis for 2011 NAMCS Mail Survey." In *Proceedings of the Section on Government Statistics*, 2096–2103. San Diego, CA: American Statistical Association.

Campbell, Denis. 2011. "NHS Told to Abandon Delayed IT Project." *The Guardian*, September 21. http://www.theguardian.com/society/2011/sep/22/nhs-it-project-abandoned.

Castro, Daniel. 2009. "Explaining International IT Application Leadership: Health IT." Washington DC: The Information Technology and Innovation Foundation. http://www.itif.org/files/2009-leadership-healthit.pdf.

Centers for Medicare and Medicaid Services. 2010a. "Medicare and Medicaid Programs; Electronic Health Record Incentive Program; Final Rule. Federal Register 75, No. 144(July 28, 2010): 44314-44358." http://www.gpo.gov/fdsys/pkg/FR-2010-07-28/pdf/2010-17207.pdf.

———. 2010b. "Medicare & Medicaid EHR Incentive Program: Meaningful Use Stage 1 Requirements Overview." http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/MU_Stage1_ReqOverview.pdf.

———. 2012a. "Health Information Technology: Standards, Implementation Specifications, and Certification Criteria for Electronic Health Record Technology, 2014 Edition: Revisions to the Permanent Certification Program for Health Information Technology. Final Rule. Federal Register 77, No. 171 (September 4, 2012): 54163-54292." http://www.gpo.gov/fdsys/pkg/FR-2012-09-04/pdf/2012-20982.pdf.

———. 2012b. “Stage 2 Overview Tipsheet.” http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/Stage2Overview_Tipsheet.pdf.

———. 2014. “Medicare and Medicaid Programs; Modifications to the Medicare and Medicaid Electronic Health Record (EHR) Incentive Program for 2014 and Other Changes to the EHR Incentive Program; and Health Information Technology: Revisions to the Certified EHR Technology Definition and EHR Certification Changes Related to Standards; Final Rule. Federal Register 78, No. 171 (September 4, 2014): 52910-52933.” http://www.gpo.gov/fdsys/pkg/FR-2014-09-04/pdf/2014-21021.pdf.

———. 2015a. “Medicare & Medicaid EHR Incentive Programs -- Presentation to the HIT Policy Committee.” February 10. http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Downloads/HITPC_February2015_Full_Deck.pdf.

———. 2015b. “Medicare and Medicaid Programs; Electronic Health Record Incentive Program-Stage 3; Proposed Rule. Federal Register 80, No. 60 (March 30, 2015): 16732-16802.” https://www.federalregister.gov/articles/2015/03/30/2015-06685/medicare-and-medicaid-programs-electronic-health-record-incentive-program-stage-3.

———. 2015a. “EHR Incentive Programs: Data and Program Reports.” Accessed February 14. http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/DataAndReports.html.

———. 2015b. “EHR Incentive Programs: Medicaid State Information.” Accessed March 1. http://cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/MedicaidStateInfo.html.

———. 2014c. “Medicare and Medicaid EHR Incentive Program Basics.” Accessed November 8. http://www.cms.gov/Regulations-and-Guidance/Legislation/EHRIncentivePrograms/Basics.html.

Charles, Dustin, Carol Bean, Scott Purnell-Saunders, and Michael Furukawa. 2012. “Vendors of Certified Electronic Health Record Technology: Trends and Distributions of Meaningful Use Attestations as of October 31, 2012.” 6. ONC Data Brief, No. 6. Office of the National Coordinator of Health Information Technology. http://www.healthit.gov/policy-researchers-implementers/briefs.

Charles, Dustin, Meghan Gabriel, and Michael F. Furukawa. 2014. “Adoption of Electronic Health Records Systems among U.S. Non-Federal Acute Care Hospitals: 2008-2013.” Washington DC: Office of the National Coordinator of Health Information Technology. http://healthit.gov/sites/default/files/oncdatabrief16.pdf.

Chaudhry, Basit, Jerome Wang, Shinyi Wu, Margaret Maglione, Walter Mjoica, Elizabeth Roth, Sally C. Morton, and Paul G. Shekelle. 2006. “Systematic Review: Impact of Health Information Technology on Quality, Efficiency, and Costs of Medical Care.” *Annals of Internal Medicine* 144 (10): E 12 – E 22.

Chen, Catherine, Terhilda Garrido, Don Chock, Grant Okawa, and Louise Liang. 2009. “The Kaiser Permanente Electronic Health Record: Transforming and Streamlining Modalities of Care.” *Health Affairs* 28 (2): 323–32.

Christensen, Michael C., and Dahlia Remler. 2009. “Information and Communications Technology in U.S. Health Care: Why Is Adoption Slow and Is Slower Better?” *Journal of Health Politics, Policy, and Law* 34 (6): 1011–34.

Churchill, Gilbert A. 1979. “A Paradigm for Developing Better Measures of Marketing Constructs.” *Journal of Marketing Research* 16 (1): 64–73.

Clark, Lee Anna, and David Watson. 1995. “Constructing Validity: Basic Issues in Objective Scale Development.” *Psychological Assessment* 7 (3): 309–19.

Coleman, James S, Elihu Katz, and Herbert Menzel. 1966. *Medical Innovation: A Diffusion Study*. Indianapolis: The Bobbs-Merrill Company.

Congressional Budget Office. 2005. “Cost Estimate for S. 1418, Wired for Health Care Quality Act.” CBO. http://www.cbo.gov/sites/default/files/s1418.pdf.

———. 2006. “Cost Estimate for H.R. 4157, Health Information Technology Promotion Act of 2006.” CBO. http://www.cbo.gov/publication/17997.

———. 2008. “Evidence on the Costs and Benefits of Health Information Technology.” Washington DC: CBO.

———. 2009. “CBO Estimate of the Effect of Health Information Technology Provisions in AARA.” June 16. http://cbo.gov/publication/42517.

Conn, Joseph. 2007. “Some ‘Guardedly Optimistic’ about New Health IT Bill.” *Modern Healthcare*, May 18. http://www.modernhealthcare.com/article/20070518/INFO/70518018.

———. 2014a. “HHS’ IT Panel Confronted with Incentive Program Complaints.” *Modern Healthcare*, February 4. http://www.modernhealthcare.com/article/20140204/NEWS/302049958.

———. 2014b. “Proposed Interoperability Overhaul Finds Boosters, Doubters.” *Modern Healthcare*, October 21. http://www.modernhealthcare.com/article/20141021/NEWS/310219945.

———. 2014c. “EHR Vendors, Tech-Savvy Providers Unite around Internet-like Interoperability,” December 4. http://www.modernhealthcare.com/article/20141204/NEWS/312049998.

Conway, Patrick. 2015. “CMS Intends to Modify Requirements for Meaningful Use.” January 29. http://blog.cms.gov/2015/01/29/cms-intends-to-modify-requirements-for-meaningful-use/.

Creswell, Julie. 2013. “A Digital Shift on Health Data Swells Profits in an Industry.” *New York Times*, February 19. http://www.nytimes.com/2013/02/20/business/a-digital-shift-on-health-data-swells-profits.html?pagewanted=all&_r=0.

Cummings, Simone M., Lucy A. Savitz, and Thomas R. Konrad. 2001. “Reported Response Rates to Mailed Physician Questionnaires.” *Health Services Research* 35 (6): 1347–55.

Cunningham, Robert. 2005. “Action Through Collaboration: A Conversation with David Brailer.” *Health Affairs* 24 (5): 1150–57.

David, Paul A. 1985. “Clio and the Economics of QWERTY.” *American Economic Review* 75 (2): 332–37.

———. 1987. “New Standards for the Economics of Standardization.” In *Economic Policy and Technological Performance*, edited by Partha Dasgupta and Paul Stoneman, 206–39. Cambridge, UK: Cambridge University Press.

Decker, Sandra L., Eric W. Jamoom, and Jane E. Sisk. 2012. “Physicians in Nonprimary Care and Small Practices and Those Age 55 and Older Lag in Adopting Electronic Health Record Systems.” *Health Affairs* 31 (5): 1108–14.

DesRoches, Catherine M, Eric G. Campbell, Christine Vogeli, Jie Zheng, Sowmya R. Rao, Alexandra E. Shields, Karen Donelan, Sara Rosenbaum, Steffanie J. Bristol, and Ashish K. Jha. 2010. “Electronic Health Records Limited Successes Suggest More Targeted Uses.” *Health Affairs* 29 (4): 639–46.

DeVellis, Robert F. 2012. *Scale Development: Theory and Applications*. 3rd ed. Thousand Oaks, CA: SAGE Publications, Inc.

Dunteman, George H. 1989. *Principal Components Analysis*. Newbury Park, CA: SAGE Publications, Inc.

Edwards, W. Sherman, and David Cantor. 1991. “Toward a Response Model in Establishment Surveys.” In *Measurement Error in Surveys*, edited by Paul P. Biemer, Robert M. Groves, Lars E. Lyberg, Nancy A. Mathiowetz, and Seymour Sudman, 211–33. New York: John Wiley & Sons.

Etheredge, Lynn M. 2010. "Creating a High-Performance System for Comparative Effectiveness Research." *Health Affairs* 29 (10): 1761–67.

Executive Order 13335 of April 27. 2004. "Incentives for the Use of Health Information Technology and Establishing the Position of the National Health Information Technology Coordinator." *Federal Register* 69 (84): 24059–61.

Federation of American Scientists. 2014. "JASON Defense Advisory Panel: Reports on Defense Science and Technology." Accessed December 7. http://www.fas.org/irp/agency/dod/jason/.

Fernandopulle, Rushika, and Neil Patel. 2010. "How the Electronic Health Record Did Not Measure Up to the Demands of Our Medical Home Practice." *Health Affairs* 29 (4): 622–28.

Fleming, Neil S., Steven D. Culler, Russell McCorkle, Edmund R. Becker, and David J. Ballard. 2011. "The Financial and Non-Financial Costs of Implementing Electronic Health Records in Primary Care Practices." *Health Affairs* 30 (3): 481–89.

Fonkych, Kateryna, and Roger Taylor. 2005. "The State and Pattern of Health Information Technology Adoption." Santa Monica, CA: RAND Corporation.

Friedberg, Mark W., Peggy G. Chen, Kristin R. Van Busum, Frances M Aunon, Chau Pham, John P. Caloyeras, Soeren Mattke, et al. 2013. "Factors Affecting Physician Professional Satisfaction and Their Implications for Patient Care, Health Systems, and Health Policy." Santa Monica, CA: RAND Corporation.

Gadermann, Anne M., Martin Guhn, and Bruno D. Zumbo. 2012. "Estimating Ordinal Reliability for Likert-Type and Ordinal Item Response Data: A Conceptual, Empirical, and Practical Guide." *Practical Assessment, Research, & Evaluation* 17 (3): 1–13.

Geroski, Paul A. 2000. "Models of Technology Diffusion." *Research Policy* 29 (4/5): 603–25.

Girosi, Federico, Robin Meili, and Richard Scoville. 2005. "Extrapolating Evidence of Health Information Technology Savings and Costs." Santa Monica, CA: RAND Corporation.

Gold, Marsha, Mynti Hossain, Dustin R. Charles, and Michael F. Furukawa. 2013. "Evolving Vendor Market for HITECH-Certified Ambulatory EHR Products." *American Journal of Managed Care* 19 (Special Issue): 353–61.

Goldzweig, Caroline, Ali Towfigh, Margaret Maglione, and Paul G. Shekelle. 2009. "Costs and Benefits of Health Information Technology: New Trends from the Literature." *Health Affairs* 28 (2): w282–93.

Griliches, Zvi. 1957. “Hybrid Corn: An Exploration in the Economics of Technological Change.” *Econometrica* 25 (4): 501–22.

Groves, Robert M., Floyd J. Fowler, Mick P. Couper, James M. Lepkowski, Eleanor Singer, and Roger Tourangeau. 2009. *Survey Methodology*. Second Edition. Hoboken, NJ: John Wiley & Sons.

Halbesleben, Jonathon R.B., and Marilyn V. Whitman. 2013. “Evaluating Survey Quality in Health Services Research: A Decision Framework for Assessing Nonresponse Bias.” *Health Services Research* 48 (3): 913–30.

Hall, Bronwyn H. 2005. “Innovation and Diffusion.” In *The Oxford Handbook of Innovation*, edited by Jan Fagerberg, David C. Mowery, and Richard R. Nelson. New York: Oxford University Press.

Hammond, W. Ed. 2005. “The Making and Adoption of Health Data Standards.” *Health Affairs* 24 (5): 1205–13.

Health Information Technology Promotion Act. 2006. “H.R. 4157. 109th Cong., 2nd Sess.” *Congressional Record* 152 (101): H5978–6004.

Heisey-Grove, Dawn, and Vaishali Patel. 2014. “Physician Motivations for Adoption of Electronic Health Records.” Washington DC: Office of the National Coordinator of Health Information Technology. http://healthit.gov/sites/default/files/oncdatabrief-physician-ehr-adoption-motivators-2014.pdf.

Hillestad, Richard, James Bigelow, Anthony Bower, Federico Girosi, Robin Meili, Richard Scoville, and Roger Taylor. 2005. “Can Electronic Medical Record Systems Transform Health Care? Potential Health Benefits, Savings, and Costs.” *Health Affairs* 24 (5): 1103–17.

Hsiao, Chun-Ju, and Esther Hing. 2014. “Use and Characteristics of Electronic Health Record Systems Among Office-Based Physician Practices: United States, 2001-2013.” NCHS Data Brief 143. National Center for Health Statistics. http://www.cdc.gov/nchs/data/databriefs/db143.htm.

Hsiao, Chun-Ju, Esther Hing, and Jill Ashman. 2014. “Trends in Electronic Health Record System Use Among Office-Based Physicians: United States, 2007-2012.” 75. National Health Statistics Reports. National Center for Health Statistics. http://www.cdc.gov/nchs/data/nhsr/nhsr075.pdf.

Huberty, Carl J. 1984. “Issues in the Use and Interpretation of Discriminant Analysis.” *Psychological Bulletin* 95 (1): 156–71.

Institute of Medicine. 1999. "To Err Is Human: Building a Safer Health System." Washington DC: National Academy Press. http://www.nap.edu/openbook.php?record_id=9728&page=1.

———. 2001. "Crossing the Quality Chasm: A New Health System for the 21st Century." Washington DC: National Academy Press.

Jamoom, Eric, Paul Beatty, Anita Bercovitz, David Woodwell, Kathleen Palso, and Elizabeth Rechtsteiner. 2012. "Physician Adoption of Electronic Health Record Systems: United States, 2011." NCHS Data Brief 98. NCHS Data Brief. Washington DC: National Center for Health Statistics. http://www.cdc.gov/nchs/data/databriefs/db98.htm.

Jamoom, Eric, Vaishali Patel, Michael F. Furukawa, and Jennifer King. 2014. "EHR Adopters vs. Non-Adopters: Impacts Of, Barriers To, and Federal Initiatives for EHR Adoption." *Healthcare* 2: 33–39.

JASON. 2014. "A Robust Health Data Infrastructure." 14-0041-EF. Agency for Healthcare Research and Quality. http://healthit.gov/sites/default/files/ptp13-700hhs_white.pdf.

Jha, Ashish K., and David Blumenthal. 2008. "International Adoption of Electronic Health Records." In *Health Information Technology in the United States: Where We Stand, 2008*, edited by David Blumenthal, Catherine DesRoches, and Vida Foubister, 104–42. Princeton, NJ: Robert Wood Johnson Foundation.

Jha, Ashish, Jonathan Perlin, Kenneth Kizer, and R Adams Dudley. 2003. "Effect of the Transformation of the Veterans Affairs Health Care System on the Quality of Care." *The New England Journal of Medicine* 348 (22): 2218–27.

Kahn, Katherine L., Justin W. Timbie, Mark W. Friedberg, Peter S. Hussey, Tara Lavelle, Peter Mendel, Liisa Hiatt, et al. 2015. "Evaluation of CMS' FQHC APCP Demonstration: Final First Annual Report." Santa Monica, CA: RAND Corporation. http://innovation.cms.gov/Files/reports/FQHCEvalRpt.pdf.

Katz, Michael L., and Carl Shapiro. 1986. "Technology Adoption in the Presence of Network Externalities." *Journal of Political Economy* 94 (4): 822–41.

———. 1994. "Systems Competition and Network Effects." *Journal of Economic Perspectives* 8 (2): 93–115.

Kay, Neil M. 2013. "Rerun the Tape of History and QWERTY Always Wins: Response to Arthur, Margolis, and Vergne." *Research Policy* 42: 1195–96.

Kellermann, Arthur L., and Spencer S. Jones. 2013. "What It Will Take To Achieve the As-Yet-Unfulfilled Promises of Health Information Technology." *Health Affairs* 32 (1): 63–67.

Kennedy, Peter. 2008. *A Guide to Econometrics*. 6th ed. Malden, MA: Blackwell Publishing.

Kent, Raymond. 2001. *Data Construction and Data Analysis for Survey Research*. New York: PALGRAVE.

Kingdon, John W. 2010. *Agendas, Alternatives, and Public Policies*. Updated second edition. New York: Longman.

Kleinke, J. D. 2005. “Dot-Gov: Market Failure and the Creation of a National Health Information Technology System.” *Health Affairs* 24 (5): 1246–62.

Kolenikov, Stanislav. 2014. “Programs and Tutorials Written by Stas Kolenikov.” Accessed September 3. http://www.unc.edu/~skolenik/stata/.

Kolenikov, Stanislav, and Gustavo Angeles. 2009. “Socioeconomic Status Measurement with Discrete Proxy Variables: Is Principal Component Analysis a Reliable Answer?” *Review of Income and Wealth* 55 (1): 128–65.

Lieber, H Stephen. 2009. “Healthcare Information Management and Systems Society (HIMSS) Letter to Senator Harry Reid,” February 4. http://www.himss.org/files/HIMSSorg/policy/d/letters/20090204_HIMSS_Reid.pdf.

Lieber, H Stephen, and Charles Christian. 2008. “Healthcare Information and Management Systems Society (HIMSS) Letter to HHS Secretary-Designate Tom Daschle,” December 17. http://www.himss.org/files/HIMSSorg/policy/d/DaschleLetter121708.pdf?src=ehplse20081229.

Liebowitz, Stanley J., and Stephen E. Margolis. 1990. “The Fable of the Keys.” *Journal of Law and Economics* 33: 1–25.

———. 1998. “Dismal Science Fictions: Network Effects, Microsoft, and Antitrust Speculation.” *Policy Analysis*, no. 324: 1–38.

Lineback, Joanna F., and Katherine J. Thompson. 2010. “Conducting Nonresponse Bias Analysis for Business Surveys.” In *Proceedings of the Section on Survey Research Methods*. Vancouver, BC: American Statistical Association. http://www.amstat.org/sections/srms/proceedings/y2010f.html.

Lynch, Kimberly, Mat Kendall, Katherine Shanks, Ahmed Haque, Emily Jones, Maggie G. Wanis, Michael Furukawa, and Farzad Mostashari. 2014. “The Health IT Regional Extension Center Program: Evolution and Lessons for Health Care Transformation.” *Health Services Research* 49 (1): 421–37.

Mandl, Kenneth D., and Isaac S. Kohane. 2012. "Escaping the EHR Trap -- The Future of Health IT." *The New England Journal of Medicine* 366 (24): 2240–42.

Mansfield, Edwin. 1961. "Technological Change and the Rate of Imitation." *Econometrica* 29 (4): 741–66.

———. 1963. "The Speed of Response of Firms to New Techniques." *Quarterly Journal of Economics* 77: 290–311.

Margolis, Stephen E. 2013. "A Tip of the Hat to Kay and QWERTY." *Research Policy* 42: 1188–90.

McFadden, Daniel. 1978. "Quantitative Methods for Analyzing Travel Behaviour of Individuals: Some Recent Developments." In *Behavioural Travel Modeling*, edited by David A. Hensher and Peter R. Stopher, 279–318. London: Croom Helm London.

McLeod, Caroline C., Carrie N. Klabunde, Gordon B. Willis, and Deborah Stark. 2013. "Health Care Provider Surveys in the United States, 2000-2010: A Review." *Evaluation and the Health Professions* 36 (1): 106–26.

Miller, Robert H., Christopher West, Tiffany Brown, Ida Sim, and Chris Ganchoff. 2005. "The Value of Electronic Health Records in Solo or Small Group Practices." *Health Affairs* 24 (5): 1127–37.

National Center for Health Statistics. 2013. "NAMCS/NHAMCS Publications List." Accessed November 4. http://www.cdc.gov/nchs/ahcd/ahcd_products.htm.

Office of the National Coordinator of Health Information Technology. 2014. "Report to Congress."

———. 2015. "2015 Edition Health Information Technology (Health IT) Certification Criteria, 2015 Edition Base Electronic Health Record (EHR) Definition, and ONC Health IT Certification Program Modifications; Proposed Rule." https://www.federalregister.gov/articles/2015/03/30/2015-06612/2015-edition-health-information-technology-health-it-certification-criteria-2015-edition-base.

O'Harrow, Robert. 2009. "The Machinery Behind Health-Care Reform." *The Washington Post*, May 16. http://www.washingtonpost.com/wp-dyn/content/article/2009/05/15/AR2009051503667.html.

O'Malley, Ann S., Joy M. Grossman, Genna R. Cohen, Nicole M. Kemper, and Hoangmai H. Pham. 2009. "Are Electronic Medical Records Helpful for Care Coordination? Experiences of Physician Practices." *Journal of General Internal Medicine* 25 (3): 177–85.

ONCHIT Interoperability and Health Information Exchange Workgroup. 2014. "JASON Report Task Force Final Report." October 21. http://healthit.gov/FACAS/calendar/2014/10/21/policy-interoperability-hie-workgroup.

Organization for Economic Cooperation and Development. 2015. "OECD Health Data: Total Expenditure per Capita, US Dollars Purchasing Power Parity." Accessed April 5. stats.oecd.org.

Redhead, C. Stephen. 2009. "The Health Information Technology for Economic and Clinical Health (HITECH) Act." Washington DC: Congressional Research Service.

Rogers, Everett M. 2003. *Diffusion of Innovations*. 5th Ed. New York: Free Press.

Rosenberg, Nathan. 1972. "Factors Affecting the Diffusion of Technology." *Explorations in Economic History* 10 (1): 3–33.

Ruttan, Vernon W. 2001. *Technology, Growth, and Development*. New York: Oxford University Press.

Ryan, Bryce, and Neal C. Gross. 1943. "The Diffusion of Hybrid Seed Corn in Two Iowa Communities." *Rural Sociology* 8 (1): 15–24.

Sapsford, Roger. 2011. *Survey Research*. 2nd ed. Thousand Oaks, CA: SAGE Publications, Inc.

Schoen, Cathy, Robin Osborn, David Squires, Michelle Doty, Petra Rasmussen, Roz Pierson, and Sandra Applebaum. 2012. "A Survey of Primary Care Doctors in Ten Countries Shows Progress in Use of Health Information Technology, Less in Other Areas." *Health Affairs* 31 (12): 2805–16.

Skolnik, Neil S., ed. 2011. *Electronic Medical Records: A Practical Guide for Primary Care*. New York: Humana Press.

Spector, Paul E. 1992. *Summated Rating Scale Construction: An Introduction*. Newbury Park, CA: SAGE Publications, Inc.

Stark, Fortney Pete. 2008. *H.R. 6898, The Health-E Information Technology Act of 2008*. http://www.gpo.gov/fdsys/pkg/BILLS-110hr6898ih/pdf/BILLS-110hr6898ih.pdf.

———. 2010. "Congressional Intent for the HITECH Act." *American Journal of Managed Care* 16 (12): SP24–28.

Stone, Andrea. 2005. "Former Foes Clinton, Gingrich Band up on Health Care Plan." *USA Today*, May 11. http://usatoday30.usatoday.com/news/washington/2005-05-11-clinton-gingrich_x.htm.

Stoneman, Paul. 2002. *The Economics of Technological Diffusion*. Oxford: Blackwell Publishers.

Stoneman, Paul, and Paul Diederen. 1994. "Technology Diffusion and Public Policy." *The Economic Journal* 104 (425): 918–30.

Sudman, Seymour, and Joan M. Phillips. 1994. "Cognitive Aspects of Organizational Reporting." In . Danvers, MA: AAPOR. www.amstat.org/sections/srms/proceedings/papers/1994_237.pdf.

Tahir, Darius. 2014. "CMS Finalizes EHR Meaningful Use Rule, Adds Some Flexibility." *Modern Healthcare*, August 29. http://www.modernhealthcare.com/article/20140829/NEWS/308299938.

Tax Policy Center. 2007. "What Is PAYGO?" http://www.taxpolicycenter.org/briefing-book/background/budget-process/paygo.cfm.

Taylor, Erin Fries, Stacy Dale, Deborah Peikes, Randall Brown, Arkadipta Ghosh, Jesse Crosson, Grace Anglin, Rosalind Keith, and Rachel Shapiro. 2015. "Evaluation of the Comprehensive Primary Care Initiative: First Annual Report." Princeton, NJ: Mathematica Policy Research. http://innovation.cms.gov/Files/reports/CPCI-EvalRpt1.pdf.

Taylor, Roger, Anthony Bower, Federico Girosi, James Bigelow, Kateryna Fonkych, and Richard Hillestad. 2005. "Promoting Health Information Technology: Is There a Case for More Aggressive Government Action?" *Health Affairs* 24 (5): 1234–45.

The Commonwealth Fund Commission on a High Performance Health System. 2011. "Why Not the Best? Results from the National Scorecard on U.S. Health System Performance, 2011." http://www.commonwealthfund.org/Publications/Fund-Reports/2011/Oct/Why-Not-the-Best-2011.aspx.

UCLA Institute for Digital Research and Education. 2014. "Stata FAQ: How Can I Perform a Factor Analysis with Categorical (or Categorical and Continuous) Variables?" Accessed September 2. http://www.ats.ucla.edu/stat/stata/faq/efa_categorical.htm.

U.S. Department of Justice, Antitrust Division. 2014. "Herfindahl-Hirschman Index." Accessed November 22. http://www.justice.gov/atr/public/guidelines/hhi.html.

U.S. House, Committee on Energy and Commerce. 2008. "PRO(TECH)T Act of 2008: Report (to Accompany H.R. 6357), 110th Cong., 2nd Sess." House Report 110-837. http://www.gpo.gov/fdsys/pkg/CRPT-110hrpt837/pdf/CRPT-110hrpt837-pt1.pdf.

Walker, Jan, Eric Pan, Douglas Johnston, Julia Adler-Milstein, David W. Bates, and Blackford Middleton. 2005. “The Value of Health Care Information Exchange and Interoperability.” *Health Affairs*, Web Exclusive.

Wired for Health Care Quality Act. 2005. “S. 1418, 109th Cong., 1st Sess.,.” *Congressional Record* 151 (153): S13260–77.

Wooldridge, Jeffrey M. 2013. *Introductory Econometrics: A Modern Approach*. 5th Ed. Mason, OH: South-Western, Cengage Learning.

Zumbo, Bruno D., Anne M. Gadermann, and Cornelia Zeisser. 2007. “Ordinal Versions of Coefficients Alpha and Theta for Likert Scales.” *Journal of Modern Applied Statistical Methods* 6 (1): 21–28.

Biography

Martin F. Cohen received his Bachelor of Arts from Harvard University in 1986 and a Master of Public Administration from Harvard's Kennedy School of Government in 1992. He has worked more than 20 years as a health policy consultant, first at Lewin-VHI and then at Kennell and Associates, where he is a vice president. His consulting work has focused primarily on the U.S. Defense Department's TRICARE program, but he also has project experience with the Centers for Medicare and Medicaid Services and the Veterans Health Administration.