CESifo Working Papers

www.cesifo.org/wp

# Adoption and Diffusion of Health Information Technology

## The Case of Primary Care Clinics

Brant Callaway

Vivek Ghosal

CESIFO WORKING PAPER NO. 3925

CATEGORY 11: INDUSTRIAL ORGANISATION

AUGUST 2012

# Adoption and Diffusion of Health Information Technology
## The Case of Primary Care Clinics

## Abstract

We empirically examine the determinants of adoption of *information technology* by *primary healthcare clinics* using a large sample of physician clinics from several States in the U.S. Ours is one of the first studies to intensively investigate primary care clinics. These clinics are important as they represent the frontlines in the delivery of services in this large and complex market. Our study generates several interesting results related to the adoption and diffusion of Health Information Technology (**HIT**), including: (1) the adoption probabilities vary considerably by the specific type of clinic; (2) in contrast to numerous studies in the broader technology adoption literature, we find little evidence to suggest a relationship between firm (clinic) size and the likelihood of adoption; (3) there appears to be no definitive relationship between the age of a clinic and the likelihood of adoption; (4) there is a strong effect of geographic location, as measured by specific types of urban and rural counties, on the likelihood of adoption; (5) market competitive forces appear to have a mixed influence on adoption; (6) there is a distinct State-specific effect suggesting that information privacy, medical malpractice laws and State initiatives may play an important role in adoption; and (7) HIT is diffusing at a faster rate over time. Our findings have the potential to provide a better understanding of the longer-run effectiveness and efficiency in the provision of healthcare, and crafting appropriate policy responses. We note some future extensions of our work.

JEL-Code: O330, I110, I180, M150, M210.

Keywords: healthcare, primary care, health information technology, electronic medical records, technology, adoption, diffusion, urban and rural locations, competition, healthcare policy.

*Brant Callaway*
*Department of Economics*
*Vanderbilt University*
*Nashville / Tennessee / USA*

*Vivek Ghosal*
*School of Economics*
*Georgia Institute of Technology*
*Atlanta / Georgia / USA*
*vivek.ghosal@econ.gatech.edu*

August 27, 2012 / Contact: http://www.econ.gatech.edu/people/faculty/ghosal
We thank participants at the following seminars and workshops for valuable comments: workshop on "Management and Economics of ICT," organized by Institute for Strategy, Technology and Organization, Munich School of Management (Munich, 2012); workshop on "ICT, R&D and Intangibles, and ICT Diffusion to the Economy," sponsored by the European Commission and OECD (Imperial College London, 2012); the Industry Studies Association Annual Conference (Pittsburgh, 2012); Korea Development Institute of Public Policy and Management (Seoul, 2011); Emory University (Atlanta, 2011); and CESifo Applied Microeconomics workshop (Munich, 2011). We thank the HIMSS Foundation for allowing us to use the data on clinics. Vivek Ghosal gratefully acknowledges the Ivan Allen College (Georgia Institute of Technology) Dean's Special Research Award for partial research support for this project.

## 1. Introduction

High and rising healthcare expenditures have become a norm in many countries, and Governments have been exploring a wide-range of initiatives to make the provision of healthcare more cost efficient, while maintaining quality. One issue that has received considerable attention as a potential quality improver and cost reducer is the increased adoption of *Health Information Technology* (henceforth, **HIT**).[1]

In this paper we examine the HIT adoption patterns and its diffusion by using a large sample of healthcare clinics[2] from different States in the U.S. The U.S. is an interesting country to study as it does not have a national healthcare system, and the physician clinics operate in private markets and make their HIT adoption decisions based on their private benefits and costs.

There is considerable research which notes that HIT allows clinics and physicians to comprehensively manage medical information and its secure exchange between healthcare consumers and providers. Detailed studies point to benefits and efficiencies such as:[3]

1. Complete and searchable health information, available at the point of diagnosis and care, allowing for more informed decision making to enhance the quality, safety and reliability of healthcare delivery;
2. Reduce unnecessary or duplicative tests or procedures;
3. Early diagnosis and characterization of disease, and computerized reminders for treatment and follow-up care, with the potential to significantly improve outcomes and reduce costs;
4. Reduction in medical errors and adverse events through an improved understanding of each patient's particular medical history, potential for drug-drug interactions, or (eventually) enhanced understanding of a patient's metabolism or even genetic profile and likelihood of a positive or potentially harmful response to a course of treatment; and
5. Increased efficiencies related to administrative and nursing tasks, allowing for more interaction with and transfer of information to patients, caregivers, and clinical care coordinators, and monitoring of patient care.

[1] In the literature there are alternative expressions such as: Health Information Technology (HIT) and Electronic Medical records (EMR). For our purposes we will use these terms synonymously and refer to them as **HIT**.
[2] "Clinics" in our sample refer only to those facilities which provide outpatient healthcare services. They <u>do not</u> include overnight stay facilities and hospitals.
[3] For example, Adler-Milstein and Bates (2010), Bates (2005), Bower (2005), Congressional Budget Office (2008), Girosi and Scoville (2005), Hill and Powell (2006), Hillestad (2008), Hillestad et al. (2005), Sidorov (2006), Steinbrook (2009), Wang et al. (2003) and Walker et al. (2005).

While the nation-wide benefits in terms of cost-savings and gains in quality of healthcare seem potentially large,[4] the HIT adoption rate in the U.S. appears to have been somewhat slow. **Figure 1** displays the rates of adoption of basic as well as more advanced HIT systems. With the caveat that it is very difficult to compare the quality and functionality of the HIT investments across countries, the cross-country HIT adoption rates by *"primary care"* practices displayed in **Figure 2** shows the U.S. to be at the lower end of the spectrum among advanced countries. In 2006, for example, only 28% of primary care physicians used HIT in their clinics in the U.S. as compared to 98% in the Netherlands, 89% in the U.K., and 42% in Germany. While there are several factors that contribute to the observed differences, an obvious factor relates to differences in national healthcare systems. Countries with national healthcare systems have subsidized many aspects of HIT adoption and require various procedures and processes to conform across the entire system. In a more market-based system such as the U.S., individual physician clinics adopt HIT based on the evaluation of their private benefits and costs.[5]

Against this backdrop, we empirically examine HIT adoption decisions using a large sample of primary care physician clinics from several large States in the U.S. While there have been studies examining the adoption of Information Technology by hospitals,[6] ours is one of the first to comprehensively examine HIT adoption by primary care physician clinics. We focus on primary care clinics for two reasons. First, they represent the frontlines in the delivery of healthcare. Studying primary care clinics, therefore, may provide important insights into the longer-run effectiveness and efficiency in the provision of healthcare. Second, the vast majority of international comparisons that have been conducted have been based using data on primary care clinics. Examining primary care, therefore, allows us to focus on some of the core issues in this large, important and complex market.

[4] The studies noted in fn. 3 estimate that nation-wide adoption of HIT systems could save the U.S. healthcare industry between $60-$100 billion per year, corresponding to about 3% of annual U.S. spending on healthcare.
[5] See Blumenthal (2009) and Blumenthal and Glaser (2007) for a discussion.
[6] For example, Angst et al. (2010), Dranove et al. (2012), and Miller and Tucker (2009a, 2009b).

The data we use are unique in that we combine various *clinic-level* characteristics (e.g., type of clinic, number of physicians in the clinic, age of clinic, date HIT was adopted, among others) with *geographic location-specific* information (e.g., urban/suburban versus rural counties, county-level data on incomes, number of clinics, health indicators, education, among others) to create a comprehensive dataset to examine factors that may influence HIT adoption decisions. The results of our study aim to shed light on some of the key drivers of HIT adoption and diffusion, and be policy-relevant in the sense that we may be able to point to specific aspects where Governmental and other initiatives can be implemented to enhance adoption of HIT.

The paper is organized as follows. In Section 2 we highlight selected results from the theoretical and empirical literatures on technology adoption. We identify characteristics such as clinic size, level of demand, the extent of product market competition, among others, that might influence clinics' decisions to adopt. Section 3 examines some of the benefits and costs of HIT adoption. Section 4 outlines our empirical methodology for examining adoption and diffusion of HIT, and section 5 describes the data. Our empirical findings are presented in Section 6. We conclude with a discussion of our findings and future extensions in Section 7.

## 2. Theoretical Results and Empirical Findings on Technology Adoption

In this section we briefly overview selected theoretical results and empirical findings on how firm size and market characteristics, including the extent of competition, affect technology adoption patterns, and note the implications for our study of HIT adoption by healthcare clinics.

### 2.1. Theoretical Results

The classic paper on technology adoption by Griliches (1957) noted two stylized facts on the adoption of hybrid corn by farmers: (i) technology appears to diffuse gradually over time across firms within an industry; and (ii) within-industry diffusion process follows an *S-shaped* curve. In the U.S. context, **Figure 1** displays the pattern of HIT adoption during 2001 to 2009. We see that by 2009 the overall level of adoption was still relatively low (about 40%) but was gaining momentum, signaling that we are likely in the initial part of the S-shaped adoption curve turning upwards.

Below we highlight selected classes of models which offer specific insights for our empirical analysis of HIT adoption by clinics:[7]

1. The first class of models relates to those which assume certainty in the value of the technology and where a firm's actions do not affect the payoffs of other firms (non-strategic). In these models, the driving force behind technology adoption relates to characteristics of the firm. A common characteristic examined is *firm size*. In Stoneman's (2002) model, for example, all firms in the industry: (i) know of the existence of a new technology; and (ii) face the same cost of adopting the new technology at a point in time. Firms are heterogeneous in their characteristics which leads to each firm having a different level of private benefits and costs that would result from adopting the new technology. Diffusion results from two mechanisms. First, the cost of adoption typically decreases over time for the same technology. Second, the quality of the new technology improves over time implying that the benefits from adopting evolve over time. A key result that can be derived from Stoneman's model is a *positive* relationship between firm size and the probability of adoption. The primary reason that larger firms are more likely to adopt are economies of scale related to the use of the new technology. In our study of HIT adoption, scale economies could arise, for example, from indivisibilities in hiring IT personnel, and purchasing software and hardware. Physician clinics may reap economies of scale from clinic size, say as measured by the number of physicians in the clinic. We empirically examine the relationship between clinic size and HIT adoption.

2. The second category of models are those which assume that firms know the value of adopting a new technology with certainty, but allow for strategic interaction among firms. The pioneering papers are by Reinganum (1981a, 1981b) and Fudenberg and Tirole (1985). Some models predict an early-mover advantage (Reinganum), while others predict a late-mover advantage (Dutta et. al., 1995). Further, some models predict that diffusion speed increases under greater competition (Gotz, 1999), while others predict that diffusion speed is slowed by competition. Milliou and Petrakis (2011) present comparative statics on the linkages between market structure and technology diffusion. Their results show that markets where firms are engaged in Cournot quantity competition may have faster diffusion of a new technology than markets where firms are engaged in differentiated product Bertrand price competition. While competition emerges as a potentially important factor, there are no clear results predicting the effect of competition on the pace of adoption. In our case, healthcare clinics are best described as providing differentiated services and broadly fit the framework described by Gotz, and

[7] Hoppe (2002) provides a insightful overview of various theoretical models and results on technology adoption.

the Bertrand results noted by Milliou and Petrakis. In our empirical analysis, we explore the connection between the degree of competition and adoption of HIT by clinics.

3. Models which assume that firms face uncertainty about the value of the new technology or the arrival date of a better version of the new technology. In Jensen's (1982) model, the firm, at each time period, can either adopt the new technology or wait and learn more about whether the technology will actually be profitable. The longer the firm waits, the more accurately it can tell whether the technology will be profitable. However, waiting comes at the cost of losing potential profits from earlier adoption of a profitable technology. In Jensen's model, diffusion of new technology occurs either because of different learning mechanisms between firms or different confidence thresholds for adopting a new technology. A notable adaptation of Jensen's model is by Weiss (1994), where firms are uncertain about both the value of the new technology and the arrival date of a better version of the technology. Weiss's model also makes it costly for firms to acquire information regarding the profitability of the new technology. This allows for some firms to never adopt. Furthermore, technologies that are likely to have major improvements in the future experience delayed adoption. These class of models are particularly appealing for HIT adoption since two of the primary reasons posited for delayed adoption of HIT are: (i) concern about the actual value of HIT for a physician clinic, and (ii) concerns about improving quality or buying a product that may becomes obsolescent when new standards of HIT emerge or more sophisticated versions of HIT are available. Unfortunately, we are not aware of detailed clinic-level micro-data which would allow us to examine the dynamics and predictions of these models.

The theoretical models noted above highlight the reasons why adoption can be quite slow in market-based systems. Heterogeneous firms, operating in markets with specific characteristics, have complicated tradeoffs when weighing their private benefits and costs and may have to weigh both uncertainty and strategic factors in their technology adoption decisions. Based on the above discussion, some of the linkages that emerge from theory for our empirical study are:

1. larger clinics are more likely to adopt HIT;
2. the relationship between the degree of competition and probability of adoption appears ambiguous and depends on a range of market-specific and behavioral factors;
3. with passage of time, as the gap between the clinics' marginal costs of operating with the old technology (e.g., paper records) and the new technology (HIT) increases, the proportion of clinics that would have adopted HIT will increase; and
4. clinics in markets with higher demand for healthcare are more likely to adopt.

### 2.1. Some Empirical Findings on Technology Adoption

We briefly review the methodology and findings from selected empirical papers in the literature on technology adoption. The first wave of technology adoption papers examined diffusion at an aggregate level where the dependent variable is the proportion of adopters of a new technology. Griliches (1957) implemented a two-stage process in modeling the adoption of hybrid corn seeds by farmers based on differences in the profitability of using the new type of seed. First, a *Logistic* curve is fitted to the data on the proportion of adopters, and multiple logistic curves were fitted for different groups (in Griliches's case, farmers were grouped by the State their farm is in). Second, a linear regression was used to explain the slope coefficients of the fitted Logistic curves representing diffusion speeds in terms on independent variables such as average farm size in the state and the difference in productivity between hybrid seed and normal seed in the state.

Subsequently, Mansfield (1968, 1977) studied fourteen innovations in four industries and found that the most consistent predictor of rapid technology diffusion was firm size, while other factors were significant in specific instances. Davies (1979) examined twenty-two innovations in UK after World War II, and his findings were consistent with Mansfield's that firm size was the single-most important factor determining diffusion rates.

Subsequent empirical analysis on technology adoption focused on the "timing" of adoption of the new technology. To address this question, *Survival Analysis* models were used. Regarding firm size, Hannan and McDowell (1984) study ATM adoption by banks. They use an exponential hazard rate model and find evidence that large banks will be more likely to implement ATMs. Rose and Rose and Joskow (1990) use a semi-parametric Cox hazard rate model to study adoption of a cost-reducing technology in the electric utility industry. By studying the electric utility industry where almost all firms are local monopolies, they are able to minimize the strategic effects that are present in other industries. They find that firm size plays a dominant role in the probability of adoption of the new technology. Thomas (1999) examines the computer disk drive industry and finds that large firms are more likely to adopt a new technology when obsolescence is slow, but under specific circumstances smaller firms will adopt earlier when obsolescence occurs more rapidly. In contrast, Oster (1982) finds a negative relationship between firm size and diffusion speed in the case of the Basic Oxygen Furnace technology in the steel industry.

Regarding product market competition, Hannan and McDowell (1984) find that banks operating in more concentrated markets were more likely to adopt ATMs. In contrast, Levin (1987) finds a negative relationship with adoption speed for both market concentration and firm market share for grocery stores' adoption of optical scanners. Karshenas and Stoneman (1993) examine the role played by firm characteristic effects on the diffusion of computer numerically controlled machine tools in the UK. Their results indicate that endogenous learning, firm size, industry growth rates, the cost of the new technology, and expected changes in the cost of the new technology are most important in explaining the speed of diffusion. However, they find little evidence of strategic interaction being an important driver of adoption. Bautista (1999) and Stoneman (2002) provide insights on many of the important theoretical and empirical papers in this literature.

Taken in collection, the existing studies provide strong support for the theoretical models that predict that the likelihood of adoption will be greater for larger firms. There is, however, mixed evidence that competitive forces tend to increase the likelihood of a firm adopting a new technology, and the estimated effects are not as strong as those for the firm size effect. In the next section we provide insights into the benefits and costs related issues for HIT adoption by healthcare clinics.

## 3. A Perspective on the Benefits and Costs of HIT Adoption

We briefly review two papers that provide useful insights into assessing the benefits and costs of HIT adoption by clinics. First, Wang et al. (2003) find that clinics which implement fully functional HIT see $86,400 net profit (from increased revenues and decreased costs) per physician over a five-year period. The benefits are lower when less than a full system is implemented. Wang et al. find that the majority of the financial benefits from HIT occur in four areas:

1. savings in drug expenditures;
2. improved utilization of radiology tests;
3. better capture of charges by the clinic;
4. decreased billing errors.

They further disaggregate the financial benefits of HIT adoption by type of reimbursement mechanism for the physician. Under capitated reimbursement,[8] HIT is primarily useful in reducing medical usage for the physician (e.g., reducing lab tests and reducing medication errors). The larger the proportion of capitated patients which the physician serves, the greater the financial benefit of HIT. Under a fee-for-service scheme, revenues increase primarily through improved billing capture, and many of the other benefits may go to insurance companies or government payers. Regardless of the reimbursement method, physicians were able to reduce paper chart pulls by an average of 600 per year and reduce transcription costs.

Wang et al. provide useful insights into assessing the costs of adopting HIT. First, there are fixed costs for HIT adoption which include the initial cost of the HIT software and hardware, training the administrative workers and doctors to use the system, and other implementation costs. These are the direct fixed costs of implementing an HIT system. Another fixed cost is what they calls "induced costs." These are all the transactions costs incurred in *switching* from a paper records system to an HIT system (also see Ozdemir, 2010), as well as a temporary reduction in overall clinic productivity for several months after the system change. They provide estimates of these costs using a combination of data from the Integrated Delivery Network and expert opinion:

1. software costs of $1,600 per physician per year;
2. implementation costs of $3,400 per physician per year;
3. ongoing maintenance and support costs of $1,500 per physician per year;

[8] Capitated reimbursement is a system where physicians are paid a set amount for each person assigned to that physician whether or not that person uses medical care for a particular time period or not.

4. hardware costs of $6,600 per provider every 3 years;
5. temporary loss of productivity equal to $11,200 in first year.

Second, Miller et al. (2005) find that it takes clinics 2.5 years on average to recover their initial HIT investment which is followed by $33,000 net profit per year. If we convert this measure to Wang et al.'s five year window, Miller et al.'s study projects a net profit of $82,500 over five years which is remarkably close to Wang et al.'s finding. In Miller et al.'s study the key financial benefits are $33,000 per year per physician that result from:

1. decrease in administrative staff hours;
2. decrease in transcription costs;
3. increased total visits due to reduced physician time per patient;
4. increased coding levels for treatments from better documentation of services performed;
5. improvements in several quality areas especially in drug related reminders, data organization, accessibility, and legibility.

Their study collected information from fourteen small physician clinics who have already adopted a HIT system and their estimates of the costs are as follows:

1. initial cost of a HIT system at $44,000, which includes;
    i. $22,000 to buy the software
    ii. $13,000 in hardware costs
    iii. $7,000 in immediate productivity loss upon switching to HIT
2. ongoing costs of $8,500 per year (91% of this is due to contracted IT staff, maintenance and support, and hardware replacement).

In addition to the above, Miller et al. note a downside of adopting HIT. Of the 14 clinics in their study, 3 experienced severe problems that were partly related to the implementation of the HIT system. In the most extreme case, one clinic had no billing or revenue for ten months and almost went out of business. This is an added short-term implementation and revenue risk that many clinics, particularly small ones, have to consider in their adoption decisions.[9]

[9] Blumenthal and Glaser (2007) argue that the approximately $82,000 plus net profits estimate noted by Wang and Miller are likely to be an upper bound to the profitability of HIT adoption due to sample selection issues related to the specific types of HIT being covered and the sample of relatively more successful clinics in the sample.

Overall, while the benefits of HIT appear considerable, adoption costs can be significant. The most obvious costs are the hardware and software investment costs. But the costs also include switching costs to a new technology and the related administrative and organizational transformation costs. Finally, there is uncertainty of post-adoption outcomes, at least in the near term.[10]

## 4. Estimation Strategy and Empirical Model to Examine HIT Adoption

In this section we outline the estimation strategies to examine various aspects of HIT adoption by the clinics in our sample, and spell out the determinants of HIT adoption.

### 4.1. Estimation Methods

Following the empirical technology adoption literature, we use standard estimation strategies to study HIT adoption by the clinics. First, the logistic regression is a commonly used method for estimating statistical models with a binary dependent variable. In our case, a clinic either adopts HIT or not. The logit specification gives rise to an *S-shaped* relationship between the probability of an event and the explanatory variables (Maddala, 1986; Long, 1997). Let the probability of HIT adoption be denoted by Pr $(y = 1|x)$, where y equals 0 if no adoption and 1 if adoption occurs, and $\boldsymbol{x}$ is a vector of explanatory variables. The probability of HIT adoption is given by:

$$Pr(y = 1|x) = \frac{e^{x\beta}}{1 + e^{x\beta}}, \qquad (1)$$

where $\boldsymbol{x}$ is the vector of explanatory variables, in our case related to *clinic-specific* and *geographic location-specific* factors which we detail later, and $\boldsymbol{\beta}$ is a vector of coefficients which is estimated using maximum likelihood techniques.

[10] While we focus on primary care clinics, Dranove et al. (2012) present details on the costs and benefits for HIT adoption by hospitals.

*Survival Analysis* is another approach to empirically model HIT adoption.[11] In survival analysis, the time that HIT adoption occurs T is a random variable having some probability distribution. The survival function is the probability that a clinic survives greater than some point in time t and is given by:

$$S(t) = \Pr(T > t) = 1 - F(t), \tag{2}$$

where F(t) is the cumulative distribution function, and $S(0) = 1$ and $S(\infty) = 0$; that is, no clinic is "at risk" before time 0 and all clinics have "failed" as time goes to infinity. Regarding the hazard function, this is the instantaneous risk that HIT adoption occurs at time t and is given by:

$$h(t) = \lim_{\Delta t \to 0} \frac{\Pr(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t}. \tag{3}$$

This gives us the probability that the HIT adoption (event T) occurs in a small range of times ($t$ to $t + \Delta t$), conditional on adoption not having occurred by time t and scaled by the length of time being considered.[12] Importantly, Survival analysis allows us to handle the censoring of data, which occurs when the date of the event has not occurred yet.

In our case, any clinic which has not adopted HIT yet is a censored observation. However, more data is needed to estimate a survival model. In particular, we must have the first year that the

[11] Karshenas and Stoneman (1993) propose survival analysis as a way of empirically testing many of the hypotheses derived from the theoretical models of technology adoption, and this methodology has been used to test technology adoption in several cases including ATMs by Hannan and McDowell (1984), electric utility companies by Rose and Joskow (1990), and CNC machines by Karshenas and Stoneman (1993).

[12] Allison (1995) gives an example of a hazard rate equal to 0.015 for catching the flu with time measured in months. Assuming that the hazard rate is constant across a month, this hazard rate should be interpreted to mean that an individual is expected to catch the flu 0.015 times in a month. If the hazard rate is constant for the entire year, the individual would be expected to catch the flu 12×0.015=0.18 times in a year. One other way to interpret the hazard rate is that $[h(t)]^{-1}$ gives the expected length of time before the event occurs. In this example, the individual would expect to the flu once every 5.55 years.

clinic was "at risk" of adopting HIT, whether or not the clinic has adopted HIT, and what year the clinic adopted. One complication regarding survival analysis that is notable for our paper is that selecting the origin of time in the model is important. It should be the point in time where clinics first become "at risk" of adopting HIT. *We use the first year that a clinic (in our sample) adopted HIT as this benchmark*. This, however, may be too early for some clinics. If it is in fact too early for some clinics, this will lead to estimates of coefficients in the model that are biased towards 0. This would mean that the effect seen in our empirical results are, if anything, too small, or an underestimate.

The particular survival model we use is the *Cox Proportional Hazard Model*,[13] a commonly used estimation method in technology adoption papers. The Cox regression is semi-parametric and the hazard rate is given by:

$$h_i(t) = \lambda_0(t) exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}) , \qquad (6)$$

where $\lambda_0(t)$ is the baseline hazard function which is left unspecified by the model except that it cannot be negative. If we take the logarithm of the above model, we get:

$$\log h_i(t) = \alpha(t) + \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} , \qquad (7)$$

where $\alpha(t) = \log \lambda_0(t)$. If we take the ratio for two clinics i and j, we have:

$$\frac{h_i(t)}{h_j(t)} = exp\left(\beta_1(x_{i1} - x_{j1}) + \cdots + \beta_k(x_{ik} - x_{jk})\right), \qquad (8)$$

[13] For a more detailed discussion, see Cox (1972) and Allison (2010).

so that $\lambda_0(t)$ cancels out. This form requires that the hazard rate for different clinics is proportional over time, and, therefore, the hazard functions should be parallel, but their shapes are not restricted. The model is estimated using partial likelihood techniques.

### 4.2. Determinants of HIT Adoption

In Section 2 we summarized some of the factors that will influence the likelihood of HIT adoption. Below we list those variables, as well as discuss some additional factors that are likely to affect physician clinics' adoption decisions and are included in our estimating equations.

*4.2(a). Clinic-specific effects*

We include the following clinic-specific variables in our estimation.

<u>1. Clinic type</u>

As noted in the data section later, we have seven different types of clinics. Even within this group of clinics, the nature of demand for their services is likely to vary. Some clinics may see a patient more frequently and for longer periods of time. This generates demand for better record-keeping, efficiency and effectiveness of services provided. In such cases, HIT would provide greater benefits to the clinic and patient management and, therefore, the incentive to adopt will be higher.. An example of this would be a Family Practice or Pediatric clinic. In contrast, a patient may visit an Urgent Care clinic rarely, typically due to unexpected healthcare needs arising after-hours or on weekends when the regular clinics are closed. In this case maintaining electronic records (HIT) may be relatively less valuable compared to a Family Clinic. To control for these aspects, we include clinic-type dummy variables in our estimated models.

2. Clinic size

As noted in Section 2, larger clinics will have a greater likelihood of adoption due to potential economies of scale. We measure clinic size by the number of physicians.[14]

3. Year clinic opened (age)

After controlling for other factors, *a priori* we may be inclined to believe that newer clinics to have a higher adoption rate of HIT. Older clinics, for example, may suffer from path-dependence and need to incur considerable switching costs to change to a new organizational and administrative structure to incorporate HIT. A new clinic starting up, on the other hand, may have more flexibility to set up operations with the available newer technologies. However, newer clinics may be more uncertain about their future revenue streams, be uncertain about survival, and have less financial stability. In addition, older clinics may, at the margin, face lesser financial constraints such as access to credit as compared to smaller ones due to available past history of revenues/profits.[15] Given the various countervailing influences for both small and large clinics, it appears difficult to predict a clear relationship between a clinic's age and the likelihood of HIT adoption.

*4.2(b). Geographic location characteristics*

A clinic operates in a specific geographic location. In our analysis, our base geographic area is a "county." A county, for example, can be in a large city metropolitan area (suburban) or be a small rural county. As is well documented in U.S. Census data, there are important differences even between counties such as those that contain a large city versus those that are in large city

[14] Data on potential other measures of size such as number of patients seen by the clinic during a year or the clinics' annual revenues are simply not available. More generally, however, using employment levels to measure firm size is quite common in the literature; see the studies cited in Caves (1998), Ghosal (2010) and Sutton (1997).
[15] The literature reviewed on firm survival and mobility in Caves (1998) and Sutton (1997), and the results on uncertainty and financing constraints in Ghosal (2010) and Ghosal and Loungani (2000), point to some of these effects being important in general.

metropolitan (suburban) areas. The large city counties tend to have a lot of business units, and the typical profile is that a lot of people who work in the large city counties actually live in the surrounding large city metropolitan area (suburbs). Large city counties often have high population and density, much larger proportion of the population being Hispanic and African-American, much lower percentage of whites, somewhat lower incomes, higher poverty rates, higher pollution indices and lower levels of educational attainment. Large city metropolitan area (suburban) counties, in contrast, tend to have quite different characteristics such as much higher incomes, greater percentage of whites, lower population density, higher levels of educational attainment and lower pollution indices. At the other extreme, rural counties have dramatically different underlying socio-economic and demographic characteristics.

Such differences, which affect the underlying fundamentals related to demand and competitive forces, across geographic locations can affect the incentives to adopt HIT. To control for these broader location related effects we consider alternative strategies and variables.

### 1. Geographic location dummies

We use the *county* the clinic is located in as the immediate market the clinic is likely to draw patients from. This definition is likely to work well as the relevant market if the county is a rural one or if we think of a county in which there is a small "town" (as distinguished from a Small City or a Large City). For urban counties, the geographic market is more complex as big city metropolitan areas traverse many counties and patients could live in one adjacent county, work in another, and could choose a clinic anywhere between these points. Further, among city markets, there is a difference in the expansiveness of the adjacent areas depending on whether it is anchored by a large city like Atlanta (which is in Fulton county with a population of 1.1 million, and has a metropolitan area with a population of 5.5 million) or a small city like Savannah (which is in Chatham county with a population of 258,000, and has a metropolitan area with a population of 344,000). In addition, if we consider the large city metropolitan area, there are important differences between the core county the city is in versus the adjacent counties (often referred to as the suburbs). The differences lie in population, demographic, income, education, among other, characteristics. A rural county in contrast is much smaller, such a Brantley county in Georgia (with a population of 16,000). In our sample of States, there is considerable variation in the distribution of large versus small cities and rural areas. Given this, we include the following five geographic location dummies in our estimated specifications (with a "town" county serving as the baseline location dummy, relative to which all others are considered):

a) large city county (LC);
b) large city metropolitan area counties (LC_Ma);
c) small city county (SC);
d) small city metropolitan area counties (SC_Ma); and
e) rural county (Rural).

Overall, the level of demand and the extent of competition is likely to be higher in the large city and its metropolitan areas as opposed to small cities and small city metropolitan areas, and considerably higher than in rural areas. These attributes link to the predictions of the theoretical models we summarized and we expect the HIT adoption rate to increase as we go from rural to small city to large city markets.

2. County-specific characteristics

While the county dummies described above are likely to capture the important effects across different geographic markets in an encompassing manner, we also experiment with explicitly including specific county characteristics that are related to demand, costs and competition.

The first set of county-level variables we consider are:

a) physician rate;
b) median income;
c) educational status; and
d) wages of medical assistants

Physician rate is the number of physicians per 10,000 population. This variable roughly proxies for the extent of competition among clinics in the area. Higher incomes and educational attainment are expected to be related to higher demand for healthcare services as well as better and more effective care. These two variables, therefore, are demand-side controls. Areas with higher wages of medical assistants are expected to see greater substitution towards automation technology (HIT) due to standard input-substitution arguments.

The second set of county-level variables relate to county health characteristics. Here we consider five variables related to the county population health status indicators:

a) percent of population who smoke;
b) percent of population who are classified as obese;
c) number of particulate matter days in a year; and
d) number of ozone days in a year; and
e) percent of population with no health insurance;.

The first four variables are designed to capture demand for healthcare arising from factors that can broadly be classified under "health status" of population. Greater incidence of chronic conditions, that may result from smoking or obesity, may increase demand for longer term healthcare. Similarly, higher pollution levels in a county, as measured by particulate matter days and ozone days, may lead to longer term health problems. These four variables may affect demand for healthcare due to the need for keeping better patient records and tracking, and potentially generate greater incentives for more efficient technologies to treat patients. The fifth variable, health insurance status (percent without insurance), is a commonly used variable noted in research and policy analysis to proxy access to healthcare. As noted in the U.S. Census data, the population who do not have health insurance are overwhelmingly those with lower income and lower education. Presence of this attribute, therefore, is likely to lead to lower demand for healthcare and at the margin we expect the incentives for clinics to invest in a relatively expensive technology (HIT) to be lower.

While the county characteristics provide an alternative look, the geographic location dummies, as we noted earlier, are likely to capture the same effects as these direct variables, as well as any unobserved effects, in a more encompassing manner.

*4.2(c). State-specific effects*

Our sample contains five U.S. States with somewhat different characteristics. While we include clinic-specific and geographic location-specific effects, there are reasons to believe that HIT adoption is likely to contain broader State-specific effects not captured in the above variables.

There are several likely influences. First, the literature shows that "privacy" laws vary across States, and earlier work examining HIT adoption by hospitals contained a distinct State-specific effect: hospitals in States with more stringent privacy laws are less likely to adopt HIT. Second, there are variations in State laws that facilitate the use of electronic records in court.[16] Third, a similar effect exists for medical malpractice effects which vary across States. Fourth, some of the States had initiated selective programs/incentives to facilitate early adoption of HIT.[17] Since there are several reasons why State-specific effects may be important, we control for this in our estimation.

## 5. Data Description

We use data on the characteristics of clinics and the geographic areas they operate in. The *clinic-specific* data are from the *Healthcare Information and Management Systems Society* (**HIMSS**) database, which is the standard database used in this literature. We use the HIMSS 2006 database as this was the most recent one available when we started this project. It turns out that using this year may also be beneficial from a conceptual standpoint. The U.S. embarked on several policy initiatives

[16] See Miller and Tucker (2009a and 2009b).
[17] See Marchibroda (2006) who notes that there were executive orders issued by 12 state governors before 2006 regarding HIT adoption, including, for example, GA, FL, TX, IL but not NY. The Robert Wood Johnson Foundation (2012) report (p.10) indicates that adoption rates are higher in 2002 (roughly our time frame) in the South than in the Midwest and northeast.

and incentives starting 2008-9. Using the 2006 data frees us from the policy-induced distortions that exist in the more recent data. By using the 2006 data we can, therefore, more closely focus on the firms' (clinics') adoption decisions based on their assessment of private benefits and costs and market conditions. As noted earlier, the focus of our study are physician clinics that fall under the broad "primary care" category. We collected information on seven specific types of clinics for our empirical analysis: (1) Family Care; (2) Primary Care; (3) Internal Medicine; (4) Multi-Specialty; (5) Pediatric; (6) Urgent Care; and (7) Women's.[18]

In the description of the data on the clinics, and our own investigation from examining specific clinics, it appeared that the "Multi-Specialty" clinics are a hybrid category. These clinics provide some mix of Family Care, Pediatric, Internal Medicine, etc. Most of the categories we could discern upon careful examination of the data relate to the broad primary care umbrella. Hence their inclusion in our sample. The typical type of "Urgent Care" clinic we observe in the U.S. provides services that are relatively similar to those provided by say a Family Practice clinic. Individuals often opt to go to these clinics as the regular primary care clinics have fixed hours. After hours and weekend related care can be provided by these Urgent Care clinics. Hence their inclusion in our sample as a broad primary care facility, but with somewhat different demand characteristics. Finally, the Women's Care category refers to various routine, primary care, types of services provided for women's healthcare. These are not specialty clinics such as Gynecology or Obstetrics. Hence their inclusion in our sample. Overall, our selection of the seven types of clinics encompass the broad rubric of primary care facilities.

[18] The broad category is "ambulatory care" which refers to any medical care delivered on an "outpatient" basis. Hospitals and any overnight stay facilities are <u>not</u> included in this sample. Facilities in this category include, for example: (1) physician offices, which is the most common facility under this category, and includes specialists in, for example, family medicine, internal medicine, obstetrics, gynecology, cardiology, gastroenterology, endocrinology, pediatric care, among others; and (2) urgent care centers. The seven types we select represents a sub-sample of the universe of types of clinics which is quite large. Given the focus of our study, which is more towards primary care issues, we did not consider many types of clinics such as endocrinology, cardiology, among many others which are very specialized and often cater to more advanced care. All of the seven categories selected by us comprise an important component of delivery of "primary care," broadly defined.

From the population of clinics comprising of the seven specific types noted above, we created a sub-sample. First, we only considered clinics with thirty or fewer physicians. This is motivated by our desire to examine relatively smaller clinics in urban and non-urban areas. In principle, more than about 10 physicians per clinic is relatively large, but we keep the 10-30 physician clinics in the sample to examine issues related to economies of scale which would more likely reveal themselves in clinics with a larger number of physicians (clinic size).[19] Our sample has a large representation of small clinics. As we note below, about 73% of the clinics in our sample have 5 or less physicians. Second, we collected data on clinics from five States: Florida, Georgia, Illinois, New York and Texas. Our interest in Georgia is motivated by the State the authors are from! The other four States represent some of the larger States in the US with considerable variation in socio-economic factors. We restrict the number of States to the above five as we include a range of other variables from different data sources and adding too many States would make our task overly burdensome. In ongoing work we are aiming to expand the scope of our study to include other States. With these two restrictions, we have a total of 1,650 clinics in our sample.

For our analysis, the adoption of Electronic Medical Records (EMR) serves as our measure of HIT adoption as EMR is the standard measure used in the literature. The HIT "adoption status" of a clinic could be in one of five states: live and operational, installation in progress, contracted/not yet installed, to be replaced, and not automated. From the adoption status information, we created a binary variable which equals 0 if the clinic was "not automated", and 1 otherwise. The database contains information on the year the clinic adopted HIT, number of physicians at the clinic, location of the clinic, the type of clinic (e.g., pediatric, family care, etc), and the year the clinic opened.

[19] Our cursory examination revealed that some of the clinics that had a large number of physicians were more multi-purpose in nature and in large city urban centers. Without knowing more details about the specific organizational form and functionality of these clinics, it seemed difficult to include them in a sample which had a disproportionately large number of relatively small clinics. In our ongoing research in this area we are examining a wider range of issues related to clinic organization forms and the chain/network characteristics (we briefly comment on this in the concluding section 7).

As noted in section 4.2, we control for *geographic market* characteristics, and define the relevant geographic market as the "county" the clinic is located in. Since the database contains information on the location of the clinic, we were able to assign the county the clinic resides in. We use this information to control for characteristics of counties such as part of a large or small metropolitan area, or rural. In addition, from the *Census* county-level data we gathered information on income, educational attainment, among others.

Finally, we collected data on county health and related statistics from the *U.S. County Health Rankings* which included the percentage of the county population who smoke, percentage obese, number of physicians per 10,000 people in the county, and two pollution measures - the number of particulate matter days per year and the number of ozone days per year.

**Tables 1 and 2** present some clinic-specific summary statistics. Considering all categories of clinics, we see that the average number of physicians in a clinic is about 5, with the range being 1 to 30 (our imposed upper-bound on size). Not unexpectedly, Multi-Specialty clinics have larger average number of physicians at 10, and Urgent Care clinics being the smallest with average of less than 4 physicians. Considering all clinics, the percentage of firms which have adopted HIT is 41%, with Urgent Care clinics at the lowest adoption rate of about 27% and Pediatric and Multi-Specialty clinics at the higher end of about 48%-50% adoption. Table 2 indicates that there is wide variation in the dates of the birth of a clinic. While some of the dates the clinic opened ("birth") are very early, the vast majority of the clinics in the sample are not old, and have an average starting date around 1995. Tables 1 and 2 also show when the clinics adopted HIT. The mean adoption date for our sample is around 2001, with a wide range from 1991 to 2006 (the end point of our sample).

To get a visual perspective and make some observations on interesting patterns, we display some data in **Figures 3-5**. Figure 3 presents information on HIT adoption by size of clinic (number of physicians). Between 1-5 physician clinics there appears to be no discernible trend in HIT adoption, the percentage is marginally higher for the larger clinics. Figure 4 presents the adoption rates by State for the clinics in our sample, and Texas emerges with the highest HIT adoption rate with Illinois and New York at the lower end. Figure 5 displays what we saw in Table 1, that there is considerable variation in adoption rates across different types of clinics, with Multi-Specialty and Pediatric clinics at the higher end of adoption rates.

## 6. Estimation Results

We first present estimates from Logit models where the dependent variable is binary indicating whether or not the clinic has adopted HIT. The results of the logit models are presented in Tables 3.1-3.4 and 4.1. Second, we estimate Survival models where the dependent variable includes whether or not the clinic has adopted HIT, the first year that it became "at risk" of adopting HIT, and the year that it adopted conditional on being an adopter. The results of the survival models are presented in Tables 5.1 and 5.2.

### 6.1. Logit Results

We present the logit results in the following sequence. First, **Table 3.1** presents the baseline model and controls for only state effects and clinic type effects. As noted in Section 4.2(c), the State-effects are designed to control for factors related to variation in privacy laws, medical malpractice laws, and selected initiatives for earlier adoption, among other factors. The clinic-type dummies control for underlying patient characteristics and demand based on the type of care provided. Second, **Table 3.2** includes added clinic-level controls related to the number of physicians (clinic size), accounting for scale economies effects, and year the clinic opened which may affect the likelihood of adoption. The specifications in **Table 3.3** augment the estimated specification by including location characteristics. As noted in section 4.2, these are dummy variables for the type of county that the clinic is located in: (i) large city, (ii) large city metropolitan area, (iii) small city, (iv) small city metro area, (v) rural and (vi) town. In all specifications that include the location dummy variables, “town” county is the excluded dummy so that the coefficients are interpreted relative to the town dummy. In **Table 3.4** we present an ancillary regression where, as noted in Section 4.2(b), the county location dummy variables are replaced with county-specific variables. Finally, in **Table 4.1** we present estimates from a subset of our full sample. Here we restrict the sample to those clinics containing 10 or less physicians. The motivation for this restriction is that we thought that clinics with relative large number of physicians were somewhat of an anomaly and these typically tended to be concentrated in very large urban areas. Given that our sample contains a preponderance of much smaller clinics, we wanted to conduct a check of robustness and investigate whether excluding the relative large clinics might affect our estimated coefficients. Below we summarize our main observations from the estimates in Tables 3.1-3.4 and 4.1.

1. Clinic type

Our reasoning was that clinics which examine patients who are more likely to be frequent and regular visitors will have a greater incentive to adopt HIT due to the need for better record-keeping abilities and efficiencies of ongoing patient management. Urgent care clinics, for example, which often draw patients requiring unexpected after-hours and weekend care are much less likely to see repeat and continuing patients than the other types of primary care clinics which would imply that HIT may be relatively less important for these clinics. Our estimates show that, as compared to Urgent Care (the baseline clinic-type dummy) and Women’s clinics, the more general practice categories – Family Practice, Primary Care, Internal Medicine – have markedly higher probabilities of HIT adoption.

Clinic-type dummy variables are included in all five of our Logit specifications. In the baseline specification (table 3.1), the coefficient on Family Practice is 0.723 indicating that a Family Practice clinic is 2.06 (= $e^{0.723}$) times more likely to have adopted HIT than an Urgent Care clinic.

This result is similar to the estimated quantitative effects for Primary Care and Pediatric clinics; the quantitative effects for Internal Medicine and Multi-Specialty clinics are somewhat higher. Each of these clinic-type dummy variables are significant at the 1% level for all five of the Logit specifications. Of these, the largest effect is for Multi-Specialty clinics which has a coefficient of 1.166, indicating that they are 3.21 times more likely to adopt HIT than Urgent Care clinics. As we noted in section 5, Multi-Specialty clinics are a hybrid category often providing several areas of care such as Family Care, Pediatrics, Internal Medicine, etc – all under the broad primary care category.

Our results are robust to adding additional explanatory variables in the later specifications. For example, the coefficient for Family Practice ranges from a minimum of 0.723 in the baseline specification (table 3.1) to a maximum of 0.929 when controlling for location characteristics (table 3.3). The effect of clinic-type is also robust to controlling for the *size* of the clinic. For example, the coefficient on Family Practice is 0.929 in table 3.3 which controls for location characteristics and uses the full sample; the coefficient on Family Practice is 0.896 in table 4.1 which also controls for location characteristics but limits the sample to clinics with ≤10 physicians.

Overall, our results indicate that clinic type has a strong influence on whether or not a clinic adopts HIT. This is consistent with our discussion in section 2 that clinics which are likely to have regular patients and a need for better record-keeping are more likely to adopt HIT. Our results are robust to different specifications additional control variables, and restricting the sample to the relatively smaller (≤10 physicians) clinics.

<u>2. Number of physicians (clinic size)</u>

We control for the number of physicians in four of our Logit specifications. As noted earlier, this variable is our measure of clinic size. The received theory on technology adoption, as well as a large empirical literature, suggests that larger firms will be more likely to adopt a new technology than smaller firms in part due to economies of scale.

We find mixed results for the number of physicians being an important determinant of HIT adoption by clinics. In table 3.2, which is our baseline specification with additional controls for Number of Physicians and Year Opened, we do not find a significant effect of the Number of Physicians. When we add controls related to geographic-location dummies or county-characteristics ( tables 3.3 and 3.4), we still find no effect. However, in table 4.1, where we limit the sample to relatively smaller clinics with ≤10 physicians, we find that the coefficient is 0.062 and significant. The implied quantitative effect, however, is relatively small, and indicates that, within this sample, an additional physician per clinic increases the relative probability of HIT adoption by 6.3%.

In light of the theory, and bulk of the empirical evidence, that larger firms (clinics) should be more likely to adopt HIT, this empirical finding is intriguing. On the other hand, when we restrict the sample to relatively smaller clinics with ≤10 physicians, we do find that larger clinics, within this group, are more likely to adopt HIT. This appears to indicate that the economies of scale that are the drivers of large-firm technology adoption in the theory may exist within the smaller physician group but then peter out at some point as the clinic size continues to grow. In addition to this explanation, there may be other factors we need to control for which may better reveal the complex effects of size. We return to this discussion in our concluding section 7.

3. Year opened (age)

We include the year that the clinic opened in four of our Logit specifications. We find little evidence that the age of the clinic is important in determining whether or not a clinic adopts HIT. The estimated coefficient is insignificant in tables 3.2-3.4, and is marginally significant but with a negative sign in table 4.1. This result is perhaps not surprising in light of the mixed effects of age noted in section 4.2. We noted that while newer clinics may establish operations with newer available technology (HIT), they may face financial constraints as well as uncertainty about the future (lower survival probability). While older clinics have higher survival probability and are likely to be less financially constrained, they may have to incur greater *switching costs*. Untangling the positive effects of higher survival probability and stronger financial position of older firms from the negative effects of additional costs that older firms face in switching technologies is a question that we are not able to answer with the available data.

4. Geographic-location of the clinic

As noted in section 4.2(b), we consider a county as the basic geographic area. We include dummy variables for the location of the clinic in the specifications in tables 3.3 and 4.1. These dummy variables are: (i) Large City County, (ii) Large City Metro Area County, (iii) Small City County, (iv) Small City Metro Area County, (v) Town County, and (vi) Rural County. Results are presented relative to the baseline (omitted) "Town County" location dummy. As discussed earlier, our location dummies encompass information related to, for example, income, demographics, competition, and demand for health services in the county where the clinic is located in. We do find considerable evidence that the location of a clinic, as measured by our county dummies, has a strong effect on the probability that it adopts HIT. In line with our predictions, clinics in rural counties, which are typically characterized by lower incomes, lower education, lower population and density, among other attributes, are significantly less likely to adopt HIT relative to the baseline in each of the four specifications having location dummy controls. In table 3.3, which includes the baseline specification with location controls, we find a coefficient of -0.770 for Rural County clinics. This indicates that clinics located in rural counties are 0.463 times as likely to adopt HIT as clinics in Town counties. We find a similar result when we limit the sample to having ten or fewer physicians.

At the other end of the spectrum, clinics located in large city metropolitan areas (large city suburbs), which are typically characterized by greater income, education levels, business density, population and density, among other attributes, are significantly more likely to adopt HIT in each specification. In table 3.3, which is the baseline specification plus county controls, we estimate a coefficient of 0.520 for Large City Metro Area clinics indicated that clinics located in Large City Metro Areas are 1.68 times as likely to adopt HIT as clinics located in Town counties.

Aside from the above two, the large city county dummy comes close to being significant at the 10% level and is positive. Our interpretation for why the large city counties by themselves are not significant is that these areas have mixed population characteristics where a significant mass of low income, low education population co-exists with much higher income and high education level population. This is in contrast to the large city metropolitan "suburban" areas noted above.[20]

Our estimated results highlight the stark difference between rural and urban/suburban HIT adoption patterns. Rural clinics are much less likely to adopt HIT even after controlling for many other explanatory variables.

## 5. State-specific effects

We find strong State-specific effects. The baseline dummy is for Illinois, and the coefficient for New York is insignificant. In all specifications we estimate, clinics located in Florida, Georgia, and Texas, in ascending order, have significantly higher probabilities of adoption. The State-specific effect does not seem to be mitigated when additional controls are added in the alternate specifications we estimate. While in this paper we do not dig deeper to parse out the specific causes, these results affirm the role of the aforementioned differences across the States in privacy laws, medical malpractice laws and selected initiatives in promoting HIT.

## 6. Other Results

In table 3.4, we replace the location dummy variables with explicit county-level characteristics. The estimated specifications include the State and clinic type dummies, as well as clinic size and age. As noted earlier, we take the physician rate (the number of physicians per 10,000

[20] Dranove et al. (2012) present insightful analysis of why hospital HIT adoption rates is higher in urban areas.

people in a county) as a rough proxy for the extent of competition facing the clinic. We find that physician rate has no effect on the probability of adopting HIT. Interpreted as a competition proxy, this result is consistent with the broader technology adoption literature which finds an ambiguous link between competition and likelihood of adoption.

Among the other interesting results, median income has a small positive impact on HIT adoption. If median wage increases by $1,000, the relative probability of HIT adoption increases by 1.8%. While the quantitative effect is small, clinics located in wealthier markets appear more likely to adopt HIT. This is consistent with a patient demand and quality of service driven argument.

The average wage of medical assistants in the county where the clinic is located also has a positive impact on the probability of adopting HIT. If the average wage of medical assistants increases by $1/hour, then the relative probability of HIT adoption increases by 22.8%. This indicates that as the cost of hiring workers increases the clinics substitute away from labor and towards HIT. This is consistent with an input-substitution theoretical result.

The health status indicators related to smoking, obesity and pollution indicators are either insignificant or have mixed signs (e.g. ozone days – positive). Overall, we do not obtain meaningful new insights by replacing the county based location dummies with more specific variables that may capture aspects of demand, costs and competition.

While more detailed analysis is needed to explore why these variables do not perform well, one observation we found in the data is that for many of the county- specific characteristics variables we include in table 3.4, there was fairly strong multicollinearity (for example between income, demographic, education and some of the health status variables), as well as strong correlations with the location dummies. Our perspective is that the location dummies included in table 3.3, while encompassing a range of effects, do a much better job of proxying for the underlying location effects.

### 6.2. Survival Analysis

The survival analysis results are presented in tables 5.1 and 5.2 which reflect the same models estimated for the full sample and for the sample restricted to clinics with ≤10 physicians, respectively. As previously noted, the Cox model requires that we have data on the adoption date for those clinics who adopt at some point in the data set. We do not have this data on all clinics in the sample and drop those clinics for which this data is missing. This leaves us with N=1462 for the full sample and N=1286 for the sample limited to ≤10 physicians. In general, the same variables that are found to have an effect in the logistic model are found to be significant in the survival model. The easiest way to interpret the parameters of the estimated model is through the Hazard Ratio which is simply calculated as $e^{\beta}$. For dummy variables, the hazard ratio gives the estimated hazard when the dummy variable equals one divided by the estimated hazard when the dummy variable equals to zero. Hazard ratios greater than one imply that observations when the dummy variable equals one have, on average, higher hazards than observations when the dummy variable equals zero controlling for the other variables. For example, in table 5.1, all estimates for clinic dummies are positive, all hazard ratios are greater than one, and therefore each clinic type has a higher estimated hazard rate than the baseline clinic type Urgent Care.

The primary reason for estimating a proportional hazard model is to see if we can find evidence for the speed of HIT adoption increasing over time. While Figure 1 provided an unconditional picture of the speed of adoption over time, the estimated Cox model allows us to control for covariates while considering the hazard function. **Figure 6** plots the logarithm of the estimated hazard function for each covariate set at its mean value for the full sample of clinics. Since the curve is convex rather than linear or concave, this gives an indication that the hazard rate is increasing over time. This is evidence that the probability of adopting HIT conditional on not currently having HIT is increasing over time.

## 7. Discussion and Future Extensions

Our focus was on primary healthcare clinics as we view them to be in the forefront of the provision of services in this important and complex market. Most policy debates we are aware of – worldwide, and not just in the U.S. – place overwhelming emphasis on provision of primary care as it affects the longer-run health status of citizens. Findings from a detailed study on primary care clinics, therefore, have the potential to provide a better understanding of the longer-run effectiveness and efficiency in the provision of healthcare, and crafting appropriate policy responses.

Our paper is one of the first to comprehensively study HIT adoption by primary care clinics. Because we investigate both non-adopting and adopting clinics, and use a data set with many more observations and controls for clinic-specific and geographic location-specific factors, our paper also gets around the criticism levied against many other HIT adoption papers which only study the benefits to clinics which have already adopted HIT. Overall, our results reveal the complexities of understanding healthcare technology adoption in market-based systems.

Based on our estimation of Logit and Survival models, some of our key findings are:

1. the specific type of clinic matters. The core service providers – Family Practice, Internal Medicine, Primary Care and Pediatrics – have greater likelihood of adoption. This tallies with our arguments related to higher and consistent level of demand and repeated patient interaction generating higher demand for HIT;
2. size of the clinic, as measured by the number of physicians, appears essentially unrelated to the likelihood of adoption of HIT. This result is a bit puzzling as we expect economies of scale to generate a positive effect.[21] Our findings are also at odds with many of the previous findings on technology adoption which show a positive effect of size;
3. age of the clinic appears unrelated to the likelihood of HIT adoption. More detailed data are needed to parse out the counteracting influences of, for example, the older clinics having better financial footing and survival probabilities but them having to incur costly switching costs to migrate to the newer technology platforms (HIT);
4. geographic location is important. The likelihood of HIT adoption is the highest in large-city metropolitan area (suburban) counties and the lowest in rural counties. The estimated gap between these two ends is stark. The result is not surprising in that there are well documented differences in overall healthcare provision between urban/suburban and rural areas, as well as

[21] Davidson and Heslinga (2007) point to important challenges related to small physician clinics.

there being fundamental differences in the underlying characteristics related to income, population density, education, among others;

5. the specific State matters. Some States showing distinctly higher adoption probability. We tie this finding to differences across States in their privacy laws, medical malpractice laws, and selected incentives that have may been provided; and
6. HIT is diffusing at a faster rate over time.

To better grasp some of the complexities of adoption of HIT, we are pursuing the following two extensions in particular:

1. our ongoing preliminary investigations reveal that apart from the different clinic-specific characteristics we controlled for, there is at least one additional important dimension. While some clinics are stand-alone, others belong to chains or networks. For example, a 3-physician clinic can either be independent or belong to a city or region wide chain or network of clinics. Since chains/networks can bestow several favorable attributes such as better branding, reaping economies of scope along with scale, financial backing, higher survival probabilities, among others, it is likely that chains may have higher HIT adoption on average. This aspect may also explain why our results on firm (clinic) size are not as predicted. Unfortunately, data on chain/network affiliation is not readily available. Since this appears to be a promising avenue for unearthing some of the complexities of HIT adoption, we are currently in the process of compiling the network/chain-affiliation data for the clinics in our sample; and
2. our data reveals that there is considerable variation in HIT adoption rates in the samples that are "rural counties only" and "large city metropolitan counties only." The *coefficient of variation* of HIT adoption in the "rural counties only" sample is about 75%, and 55% in the "large city metropolitan counties only" sample. Our estimates starkly revealed the low probability of HIT adoption in rural counties.[22] But since there is meaningful variation in HIT adoption across rural counties, a closer examination of rural counties only and discovering which variables account for the within-rural differences can add significant value to our study. Similarly, for the within-urban/suburban variation.

These two extensions are likely to add considerable value to understanding the underlying forces that govern the adoption of Health Information Technology by clinics and aid formulation of appropriate policy responses at the State and National levels.

[22] Garrett et al. (2006) provide an insightful discussion of additional issues facing rural clinics.

**References**

Adler-Milstein, Julia, and David W. Bates. "Paperless Healthcare: Progress and Challenges of an IT-enabled Healthcare System," *Business Horizons* 53, 2010, 119-130.

Angst, Corey M., Ritu Agarwal, V. Sambamurthy and Ken Kelley. "Social Contagion and Information Technology Diffusion: The Adoption of Electronic Medical Records in U.S. Hospitals," *Management Science* 56, 2010, 1219–1241.

Bates, David. "Physicians and Ambulatory Electronic Health Records," *Health Affairs*, 2005, 1180-1189.

Blumenthal, David. "The Federal Role in Promoting Health Information Technology." New York: The Commonwealth Fund Perspectives on Health Reform, 2009.

Blumenthal, David and J.P. Glaser. "Information Technology Comes to Medicine," *The New England Journal of Medicine*, 2007, 2527-2534.

Bower, Anthony. *The Diffusion and Value of Healthcare Information Technology*. Rand Corporation, 2005.

Caves, Richard. "Industrial Organization and New Findings on the Turnover and Mobility of Firms," *Journal of Economic Literature*, 1998, 1947-1982.

Cox, D.R.  "Regression Models and Life-Tables," *Journal of the Royal Statistical Society*, 1972, 187-220.

Davidson, Elizabeth, and Dan Heslinga. "Bridging the IT Adoption Gap for Small Physician Practices: An Action Research Study on Electronic Health Records," *Information Systems Management* 24, 2007, 15-28.

Davies, Stephen. *The Diffusion of Process Innovations*. Cambridge University Press, 1979.

Dranove, David, Chris Forman, Avi Goldfarb and Shane Greenstein. "The Trillion Dollar Conundrum: Complementarities and Health Information Technology," National Bureau of Economic Research, Working Paper No. 18281, 2012.

Dutta, Prajit, Saul Lach and Aldo Rustichini. "Better Late than Early: Vertical Differentiation in the Adoption of a New Technology," *Journal of Economics and Management Strategy*, 1995, 563-589.

Fabiani, Silvia, Fabiano Schivardi and Sandro Trento. "ICT Adoption in Italian Manufacturing: Firm-Level Evidence, *Industrial and Corporate Change*, 2005, 225-249.

Fudenberg, Drew and Jean Tirole. "Preemption and Rent Equalization in the Adoption of New Technology," *Review of Economic Studies*, 1985, 383-401.

Garrett, Paula, Andrew Brown, Susan Hart-Hester, Elgenaid Hamadain, Corey Dixon, William Pierce, and William J. Rudman. "Identifying Barriers to the Adoption of New Technology in Rural Hospitals: A Case Report," *Perspectives in Health Information Management* 3, 2006, 1-11.

Ghosal, Vivek. "Small is Beautiful but Size Matters: The Asymmetric Impact of Uncertainty and Sunk Costs on Small and Large Businesses." Working Paper, Georgia Institute of Technology, 2010.

Ghosal, Vivek, and Prakash Loungani. "The Differential Impact of Uncertainty on Investment in Small and Large Firms." *Review of Economics and Statistics* 82, 2000, 338 – 343.

Girosi F, Meili R, and Scoville R. *Extrapolating Evidence of Health Information Technology Savings and Costs*. RAND Corporation, MG-410-HLTH, 2005.

Gotz, Georg. "Monopolistic Competition and the Diffusion of New Technology," *Rand Journal of Economics*, 1999, 679-693.

Griliches, Zvi. "Hybrid Corn: An Exploration in the Economics of Technological Change," *Econometrica*, 1957, 501-522.

Hall, Bronwyn H. and Beethika Khan. "Adoption of New Technology," *National Bureau of Economic Research*, Working Paper No. 9730, 2003.

Hannan, Timothy and John McDowell. "The Determinants of Technology Adoption: The Case of the Banking Firm," *Rand Journal of Economics*, 1984, 328-335.

Hill, John, and Phillip Powell. "The National Healthcare Crisis: Is eHealth a Key Solution?," *Business Horizons* 52, 2009, 265—277

Hillestad, Richard. "The Potential Benefits and Costs of Increased Adoption of Health Information Technology," Testimony presented before the Senate Finance Committee on July 17, 2008.

Hillestad R, J. Bigelow, A. Bower, F. Girosi, R. Meili, R. Scoville, and R. Taylor R. "Can Electronic Medical Record Systems Transform Healthcare? An Assessment of Potential Health Benefits, Savings, and Costs," *Health Affairs*, 2005, 1103-1117.

Hoppe, Heidrun. "The Timing of New Technology Adoption: Theoretical Models and Empirical Evidence," *The Manchester School*, 2002, 56-76.

Jensen, M. "Adoption and Diffusion of an Innovation of Uncertain Profitability," *Journal of Economic Theory*, 1982, 182-193.

Karshenas, M. and P. Stoneman. "Rank, Stock, Order and Epidemic Effects in the Diffusion of New Process Technologies," *Rand Journal of Economics*, 1993, 503-528.

Long, J. Scott. *Regression Models for Categorical and Limited Dependent Variables*. Sage Publications, Inc., 1997.

Maddala, G.S. Limited-Dependent and Qualitative Variables in Econometrics. Cambridge University Press, 1986.

Mansfield, Edwin. *Industrial Research and Technological Innovation: An Econometric Analysis*. London: Longman Publishers, 1968.

Mansfield, Edwin. *The Production and Application of New Industrial Technologies*. Norton, 1977.

Marchibroda, Janet. "State-level Strategies to Support HIT Adoption and Use." A New York Summit on eHealth, 2006.

Miller, Amalia, and Catherine Tucker. "Privacy Protection and Technology Diffusion: The case of Electronic Medical Records," *Management Science* 55, 2009(a), 1077-1093.

Miller, Amalia, and Catherine Tucker. "Electronic Discovery and Electronic Medical Records: Does the Threat of Litigation affect Firm Decisions to Adopt Technology?," Working Paper, MIT, 2009(b).

Miller, Robert, Christopher West, Tiffany Martin Brown, Ida Sim, and Chris Ganchoff. "The Value of Electronic Health Records in Solo or Small Group Practices," *Health Affairs*, 2005, 1127-1137.

Milliou, Chrysovalantou and Emmanuel Petrakis. "Timing of Technology Adoption and Product Market Competition," *International Journal of Industrial Organization* 29, 2011, 513–523..

Oster, S. "The Diffusion of Innovation among Steel Firms: The Basic Oxygen Furnace," *Bell Journal of Economics*, 1982, 45-56.

Ozdemir, Zafer, John Barron and Subhajyoti Bandyopadhyay. "An Analysis of Adoption of Digital Health Records under Switching Costs," Working Paper, University of Florida, 2010.

Quirmbach, H. "The Diffusion of New Technology and the Market for an Innovation," *Rand Journal of Economics*, 1986, 33-47.

Reinganum, Jennifer. "Market Structure and the Diffusion of New Technology," *Bell Journal of Economics*, 1981(a), 618-624.

Reinganum, Jennifer. "On the Diffusion of New Technology: A Game Theoretic Approach," *Review of Economic Studies*, 1981(b), 395-405.

Robert Wood Johnson Foundation. "Health Information Technology in the United States: Driving Toward Delivery System Change," 2012.

Rose, Nancy and Paul Joskow. "The Diffusion of New Technologies: Evidence from the Electric Utility Industry," *Rand Journal of Economics*, 1990, 354-373.

Sidorov, Jaan. "It Ain't Necessarily So: The Electronic Health Record and the Unlikely Prospect of Reducing Healthcare Costs," *Health Affairs*, 2006, 1079-1085.

Sutton, John. "Gibrat's Legacy," *Journal of Economic Literature*, 1997, 40-59.

Steinbrook, Robert. “Health Care and the American Recovery and Reinvestment Act,” *New England Journal of Medicine*, 2009, 1057-1060.

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

The Dorenfest Institute for HIT. Research and Education, HIMSS Foundation, Chicago, Illinois, 2009.

Thomas, L. “Adoption Order of New Technologies in Evolving Markets,” *Journal of Economic Behavior and Organisation*,1999, 453-482.

Walker, Jan, Eric Pan, Douglas Johnston, Julia Adler-Milstein, David W. Bates and Blackford Middleton. “The Value Of Health Care Information Exchange And Interoperability,” *Health Affairs*, 2005, 10-18.

Wang, S., et al., “A Cost-Benefit Analysis of Electronic Medical Records in Primary Care,” *The American Journal of Medicine*, 2003, 397-403.

Weiss, Allen. “The Effects of Expectations on Technology Adoption: Some Empirical Evidence,” *The Journal of Industrial Economics*, 1994, 341-360.

**List of Figures**

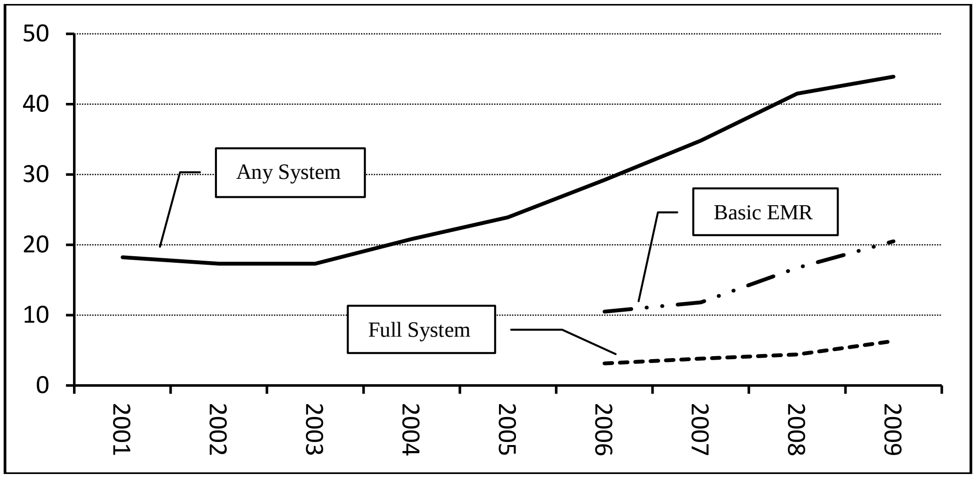


**Figure 1.** U.S. adoption rates (%) of HIT systems by system capability.

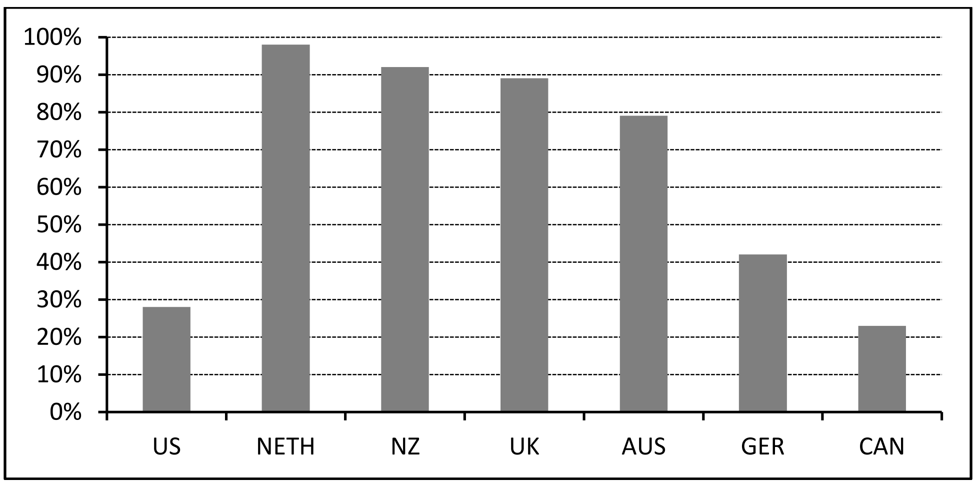


**Figure 2.** Cross-country comparison of primary care physician clinic HIT adoption levels. The reference year for the data is 2006. The Countries are: United States (US, 28%), Netherlands (NETH, 98%), New Zealand (NZ, 92%), United Kingdom (UK, 89%), Australia (AUS, 79%), Germany (GER, 42%), and Canada (CAN, 23%).

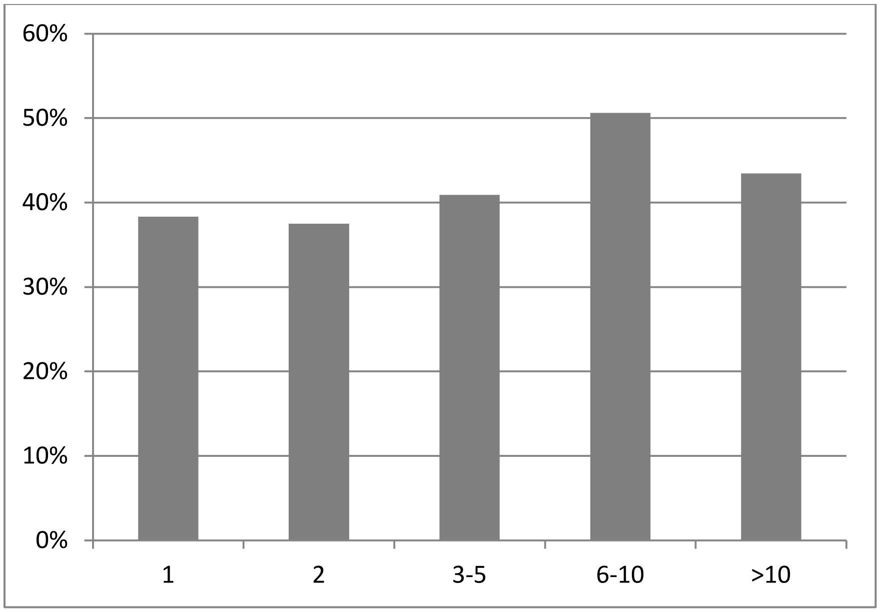


**Figure 3.** Percentage with HIT by number of physicians.

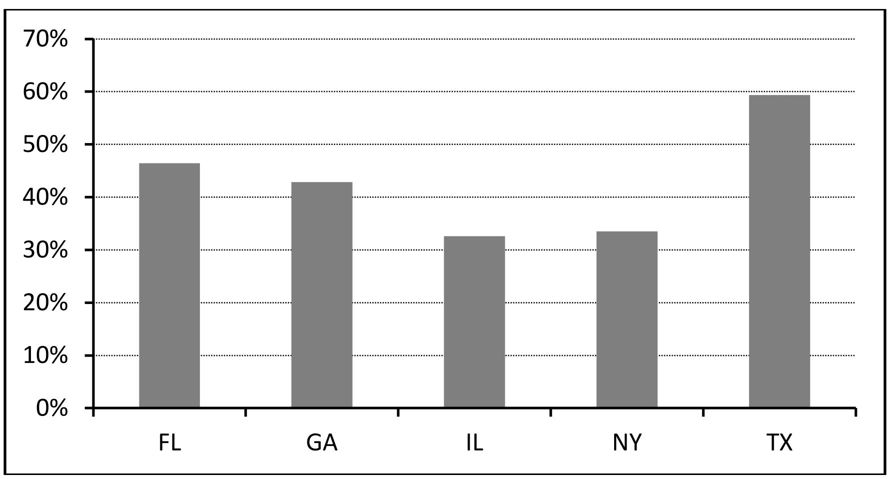


**Figure 4.** Percent of clinics automated by State. The States are Florida (FL, 46%), Georgia (GA, 43%) Illinois (IL, 32%), New York (NY, 33%) and Texas (TX, 59%).

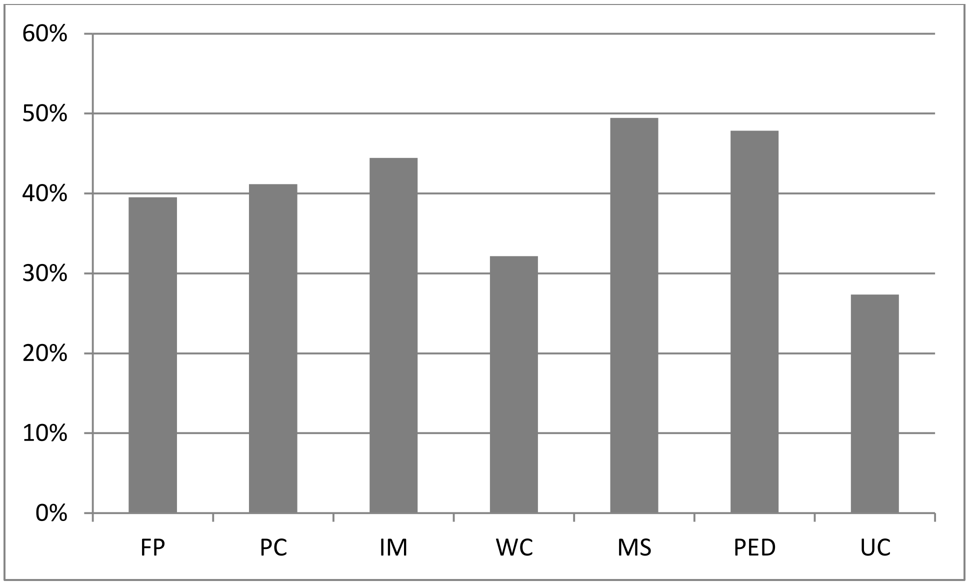


**Figure 5.** Percent of clinics adopting HIT by type of clinic.
The clinic-type abbreviations are: FP (Family Practice); PC (Primary Care); IM (Internal Medicine); WC (Women's Care); MS (Multi-Specialty); PED (Pediatric); and UC (Urgent Care).

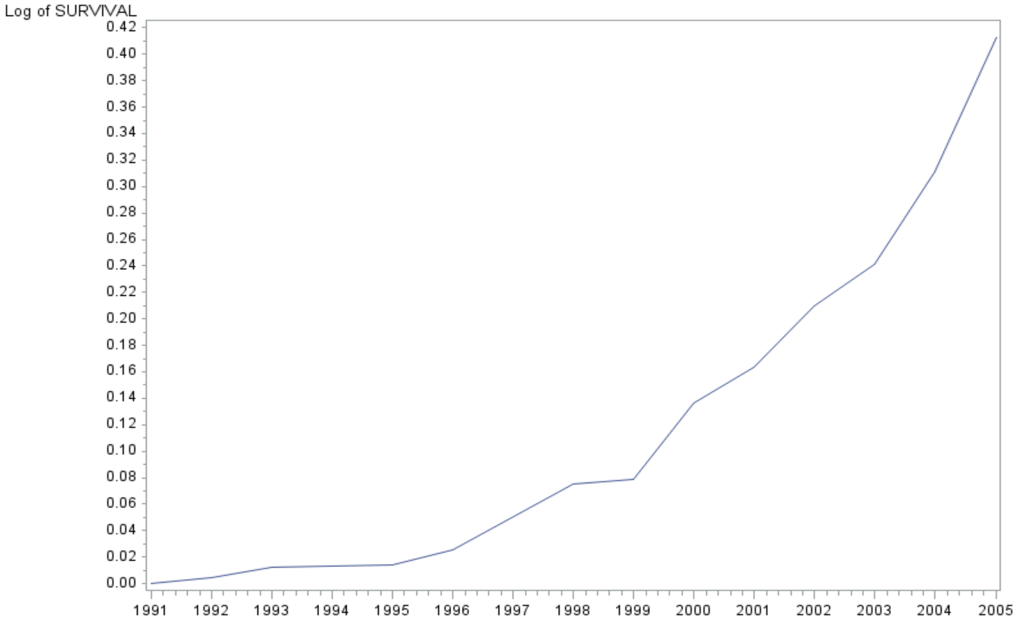


**Figure 6.** Log of the Hazard rate for full sample of clinics in the Survival Analysis. Each covariate is taken at its mean value.

## List of Tables: Summary Statistics

**Table 1. Clinic Profile**
**Summary Statistics**

| | 1. Year Opened | | 2. No. Physicians | | 3. HIT Usage (%) | | 4. HIT Contract Year | |
|---|---|---|---|---|---|---|---|---|
| **Clinic Type** | Mean | C.V. | Mean | C.V. | Mean | C.V. | Mean | C.V. |
| **All** Categories | 1995.8 | 32 | 5.04 | 113 | 41.39 | 119 | 2001.8 | 13 |
| Family Clinic | 1996.4 | 29 | 3.70 | 129 | 39.54 | 124 | 2002.7 | 12 |
| Internal Medicine | 1997.2 | 20 | 3.82 | 89 | 44.44 | 112 | 2001.8 | 14 |
| Multi-Specialty | 1994.8 | 41 | 9.97 | 76 | 49.45 | 101 | 2001.9 | 12 |
| Pediatric Care | 1995.9 | 35 | 4.65 | 107 | 47.85 | 104 | 2000.1 | 8 |
| Primary Care | 1994.9 | 33 | 4.35 | 113 | 40.90 | 122 | 2001.6 | 14 |
| Urgent Care | 1995.6 | 31 | 3.66 | 104 | 27.36 | 163 | 2003.2 | 14 |
| Women's Care | 1996.9 | 23 | 4.70 | 101 | 32.17 | 145 | 2001.4 | 15 |

Notes:
1. Summary statistics are based on data from all states in our sample: Florida, Georgia, Illinois, New York and Texas.
2. Variables in the column headers are as follows: (a) "Year Opened" represents the year the particular clinic was opened; (b) "No. Physicians" represents the number of physicians in a clinic; (c) "HIT Usage" denotes percent of clinics using Health Information Technology; and (d) "HIT Contract Year" is the year the HIT system was installed.
3. The rows represent types of clinics, with the first row (All Categories) representing the overall picture.
4. C.V. denotes the coefficient of variation, expressed as percent. For example, for "All Categories" (first row), the mean HIT usage for the full sample (all clinics) is 41.39% with a coefficient of variation (C.V.) of 119%, indicating wide variation across clinics in terms of HIT usage.

**Table 2. Clinic Profile**
**Range of Variables**

| | **Year Opened** | | **No. Physicians** | | **HIT Contract Year** | |
|---|---|---|---|---|---|---|
| **Clinic Type** | Min. | Max. | Min. | Max. | Min. | Max. |
| All Categories | 1916 | 2006 | 1 | 30 | 1991 | 2006 |
| Family Practice | 1960 | 2006 | 1 | 30 | 1996 | 2006 |
| Internal Medicine | 1980 | 2006 | 1 | 27 | 1996 | 2005 |
| Multi-Specialty | 1916 | 2005 | 1 | 30 | 1993 | 2006 |
| Pediatric Care | 1927 | 2006 | 1 | 30 | 1998 | 2005 |
| Primary Care | 1921 | 2006 | 1 | 30 | 1991 | 2006 |
| Urgent Care | 1968 | 2005 | 1 | 24 | 1996 | 2006 |
| Women's Care | 1980 | 2005 | 1 | 28 | 1996 | 2005 |

Notes:
1. The data in this table show the range of variation in the clinic profile. For example, the oldest Primary Care clinic in our sample was established in 1921 and the most recent in 2006 (this is also the last year for the HIMSS sample). In terms of the number of physicians in a Primary Care clinic, the lowest is 1 and the largest is 30.
2. The "HIT Contract Year" refers to the number of clinics adopting by year.

## List of Tables: Estimation Results

**Table 3.1. Logit Estimates**
**Sample: All Clinic Sizes**

| | Estimate (Std. Error) | Wald $\chi^2$ (Pr> $\chi^2$) |
|---|---|---|
| *State Dummies* | | |
| Georgia | 0.528 (0.183)*** | 8.343 (0.003) |
| Florida | 0.760 (0.182)*** | 17.348 (0.001) |
| Texas | 1.128 (0.154)*** | 53.402 (0.001) |
| New York | 0.034 (0.143) | 0.056 (0.812) |
| *Clinic-Type Dummies* | | |
| Family Practice | 0.723 (0.245)*** | 8.709 (0.003) |
| Primary Care | 0.831 (0.254)*** | 10.682 (0.001) |
| Internal Medicine | 1.063 (0.296)*** | 12.850 (0.001) |
| Women's | 0.368 (0.307) | 1.439 (0.230) |
| Multi-Specialty | 1.166 (0.261)*** | 19.896 (0.001) |
| Pediatric | 0.869 (0.282)*** | 9.475 (0.002) |
| *Clinic Characteristics* | | |
| No. Physicians | - | - |
| Year Opened | - | - |
| *Geographic Location Controls* | | |
| Large City County | - | - |
| Large City Metro Area Counties | - | - |
| Small City County | - | - |
| Small City Metro Area Counties | - | - |
| Rural County | - | - |
| | | |
| Number of Clinics in Sample | 1650 | |
| Likelihood Ratio (Pr> $\chi^2$) | 103.069 (0.001) | |
| Wald (Pr> $\chi^2$) | 96.928 (0.001) | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; (b) Clinic-Type: Urgent Care; and (c) Geographic: Town County.
2. The specification includes an intercept (not reported). The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

| **Table 3.2. Logit Estimates**<br>**Sample: All Clinic Sizes** | | |
|---|---|---|
| | Estimate (Std. Error) | Wald $\chi^2$ (Pr> $\chi^2$) |
| *State Dummies* | | |
| Georgia | 0.531 (0.184)*** | 8.358 (0.003) |
| Florida | 0.757 (0.183)*** | 17.104 (0.001) |
| Texas | 1.136 (0.155)*** | 530854 (0.001) |
| New York | 0.024 (0.144) | 0.028 (0.867) |
| *Clinic-Type Dummies* | | |
| Family Practice | 0.735 (0.245)*** | 8.959 (0.003) |
| Primary Care | 0.817 (0.254)*** | 10.296 (0.001) |
| Internal Medicine | 1.085 (0.297)*** | 13.304 (0.001) |
| Women's | 0.370 (0.308) | 1.441 (0.229) |
| Multi-Specialty | 1.066 (0.268)*** | 15.740 (0.001) |
| Pediatric | 0.858 (0.283)*** | 9.203 (0.002) |
| *Clinic Characteristics* | | |
| No. Physicians | 0.015 (0.009) | 2.324 (0.127) |
| Year Opened | -0.011 (0.008) | 1.990 (0.158) |
| *Geographic Location Controls* | | |
| Large City County | - | - |
| Large City Metro Area Counties | - | - |
| Small City County | - | - |
| Small City Metro Area Counties | - | - |
| Rural County | - | - |
| | | |
| Number of Clinics in Sample | 1650 | |
| Likelihood Ratio (Pr> $\chi^2$) | 107.98 (0.001) | |
| Wald (Pr> $\chi^2$) | 101.00 (0.001) | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; (b) Clinic-Type: Urgent Care; and (c) Geographic: Town County.
2. The specification includes an intercept (not reported). The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

**Table 3.3. Logit Estimates**
**Sample: All Clinic Sizes**

| | Estimate (Std. Error) | Wald $\chi^2$ (Pr> $\chi^2$) |
|---|---|---|
| *State Dummies* | | |
| Georgia | 0.616 (0.189)*** | 10.558 (0.001) |
| Florida | 0.801 (0.188)*** | 18.163 (0.001) |
| Texas | 1.230 (0.159)*** | 59.323 (0.001) |
| New York | 0.028 (0.146) | 0.038 (0.844) |
| *Clinic-Type Dummies* | | |
| Family Practice | 0.929 (0.251)*** | 13.681 (0.001) |
| Primary Care | 0.889 (0.258)*** | 11.857 (0.001) |
| Internal Medicine | 1.175 (0.300)*** | 15.290 (0.001) |
| Women's | 0.433 (0.311) | 1.947 (0.163) |
| Multi-Specialty | 1.152 (0.272)*** | 17.871 (0.001) |
| Pediatric | 0.876 (0.286)*** | 9.375 (0.002) |
| *Clinic Characteristics* | | |
| No. Physicians | 0.007 (0.010) | 0.549 (0.458) |
| Year Opened | -0.013 (0.008) | 2.494 (0.114) |
| *Geographic Location Controls* | | |
| Large City County | 0.273 (0.183) | 2.209 (0.137) |
| Large City Metro Area Counties | 0.520 (0.200)*** | 6.742 (0.009) |
| Small City County | 0.048 (0.197) | 0.060 (0.805) |
| Small City Metro Area Counties | 0.029 (0.254) | 0.013 (0.909) |
| Rural County | -0.770 (0.303)*** | 6.455 (0.011) |
| | | |
| Number of Clinics in Sample | 1650 | |
| Likelihood Ratio (Pr> $\chi^2$) | 132.99 (0.001) | |
| Wald (Pr> $\chi^2$) | 120.56 (0.001) | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; (b) Clinic-Type: Urgent Care; and (c) Geographic: Town County.
2. The specification includes an intercept (not reported). The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

| **Table 3.4. Logit Estimates<br>Sample: All Clinic Sizes** | | |
|---|---|---|
| | Estimate (Std. Error) | Wald $\chi^2$ (Pr> $\chi^2$) |
| *State Dummies* | | |
| Georgia | 0.651 (0.23)*** | 8.014 (0.005) |
| Florida | 0.995 (0.256)*** | 15.071 (0.001) |
| Texas | 1.26 (0.295)*** | 18.251 (0.001) |
| New York | 0.217 (0.195) | 1.238 (0.266) |
| *Clinic-Type Dummies* | | |
| Family Practice | 0.791 (0.249)*** | 10.06 (0.001) |
| Primary Care | 0.777 (0.259)*** | 9.025 (0.003) |
| Internal Medicine | 1.147 (0.303)*** | 14.347 (0.001) |
| Women's | 0.327 (0.313) | 1.087 (0.297) |
| Multi-Specialty | 1.037 (0.272)*** | 14.563 (0.001) |
| Pediatric | 0.819 (0.29)*** | 7.968 (0.005) |
| *Clinic Characteristics* | | |
| No. Physicians | 0.014 (0.01) | 1.756 (0.185) |
| Year Opened | -0.012 (0.008) | 2.123 (0.145) |
| *Geographic Location Controls* | | |
| Physician Rate | -0.394 (1.592) | 0.061 (0.805) |
| Median Income | 0.018 (0.009)** | 4.511 (0.035) |
| High School Graduation Rate | 0.003 (0.004) | 0.463 (0.496) |
| Percentage College | -0.024 (0.014)* | 3.097 (0.078) |
| Medical Worker Wage | 0.205 (0.066)*** | 9.7 (0.002) |
| Percent Uninsured | 0.016 (0.02) | 0.659 (0.416) |
| Percent Smoke | -0.011 (0.019) | 0.349 (0.554) |
| Percent Obese | 0.033 (0.034) | 0.979 (0.322) |
| Particulate Days | 0 (0.011) | 0.002 (0.969) |
| Ozone Days | 0.008 (0.005)* | 2.884 (0.089) |
| | | |
| Number of Clinics in Sample | 1650 | |
| Likelihood Ratio (Pr> $\chi^2$) | 140.117 (0.0001) | |
| Wald (Pr> $\chi^2$) | 126.051 (0.0001) | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; and (b) Clinic-Type: Urgent Care.
2. The specification includes an intercept (not reported). The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

**Table 4.1. Logit Estimates**
**Sample: Clinic Size of ≤10 Physicians**

| | Estimate (Std. Error) | Wald $\chi^2$ (Pr> $\chi^2$) |
|---|---|---|
| *State Dummies* | | |
| Georgia | 0.631 (0.203)*** | 9.614 (0.001) |
| Florida | 0.867 (0.202)*** | 18.447 (0.001) |
| Texas | 1.265 (0.171)*** | 54.470 (0.001) |
| New York | 0.031 (0.158) | 0.037 (0.846) |
| *Clinic-Type Dummies* | | |
| Family Practice | 0.896 (0.258)*** | 12.073 (0.001) |
| Primary Care | 0.825 (0.264)*** | 9.745 (0.001) |
| Internal Medicine | 1.110 (0.305)*** | 13.133 (0.001) |
| Women's | 0.452 (0.321) | 1.978 (0.159) |
| Multi-Specialty | 1.023 (0.292)*** | 12.265 (0.001) |
| Pediatric | 0.859 (0.296)*** | 8.413 (0.003) |
| *Clinic Characteristics* | | |
| No. Physicians | 0.062 (0.026)** | 5.781 (0.016) |
| Year Opened | -0.017 (0.009)* | 2.838 (0.092) |
| *Geographic Location Controls* | | |
| Large City County | 0.257 (0.194) | 1.759 (0.184) |
| Large City Metro Area Counties | 0.519 (0.211)** | 6.007 (0.014) |
| Small City County | 0.013 (0.206) | 0.004 (0.949) |
| Small City Metro Area Counties | -0.063 (0.263) | 0.058 (0.809) |
| Rural County | -0.739 (0.306)** | 5.817 (0.016) |
| | | |
| Number of Clinics in Sample | 1462 | |
| Likelihood Ratio (Pr> $\chi^2$) | 129.79 (0.001) | |
| Wald (Pr> $\chi^2$) | 116.52 (0.001) | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; (b) Clinic-Type: Urgent Care; and (c) Geographic: Town County.
2. The specification includes an intercept (not reported). The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

**Table 5.1. Survival Analysis**
**Sample: All Clinic Sizes**

| | Estimate (Std. Error) | $\chi^2$ (Pr> $\chi^2$) | Hazard Ratio |
|---|---|---|---|
| *State Dummies* | | | |
| Georgia | 0.743 (0.159)*** | 21.726 (0.001) | 2.103 |
| Florida | 0.786 (0.172)*** | 20.964 (0.001) | 2.196 |
| Texas | 1.026 (0.134)*** | 57.962 (0.001) | 2.790 |
| New York | -0.159 (0.149) | 1.138 (0.285) | 0.853 |
| *Clinic-Type Dummies* | | | |
| Family Practice | 0.937 (0.266)*** | 12.363 (0.001) | 2.554 |
| Primary Care | 0.923 (0.266)*** | 12.012 (0.001) | 2.519 |
| Internal Medicine | 1.217 (0.300)*** | 16.453 (0.001) | 3.377 |
| Women’s | 0.689 (0.313)** | 4.857 (0.027) | 1.993 |
| Multi-Specialty | 1.199 (0.274)*** | 19.130 (0.001) | 3.319 |
| Pediatric | 1.173 (0.282)*** | 17.324 (0.001) | 3.234 |
| *Clinic Characteristics* | | | |
| No. Physicians | 0.001 (0.008) | 0.012 (0.912) | 1.001 |
| Year Opened | 0.016 (0.008)** | 4.299 (0.038) | 1.017 |
| *Geographic Location Controls* | | | |
| Large City County | 0.457 (0.173)*** | 6.932 (0.008) | 1.580 |
| Large City Metro Area Counties | 0.392 (0.184)** | 4.532 (0.033) | 1.481 |
| Small City County | -0.147 (0.192) | 0.585 (0.444) | 0.863 |
| Small City Metro Area Counties | -0.236 (0.281) | 0.704 (0.401) | 0.790 |
| Rural County | -0.724 (0.310)** | 5.437 (0.019) | 0.485 |
| | | | |
| Number of Clinics in Sample | 1462 | | |
| Likelihood Ratio (Pr> $\chi^2$) | 176.867 (0.001) | | |
| Wald (Pr> $\chi^2$) | 171.035 (0.001) | | |

Notes:
1. The baseline dummies are as follows: (a) State: Illinois; (b) Clinic-Type: Urgent Care; and (c) Geographic: Town County.
2. The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.

| **Table 5.2. Survival Analysis**<br>**Sample: Clinic Size of ≤10 Physicians** | | | |
|---|---|---|---|
| | Estimate (Std. Error) | $\chi^2$ (Pr> $\chi^2$) | Hazard Ratio |
| *State Dummies* | | | |
| Georgia | 0.768 (0.173)*** | 19.635 (0.0001) | 2.155 |
| Florida | 0.885 (0.189)*** | 21.878 (0.0001) | 2.422 |
| Texas | 1.063 (0.145)*** | 53.568 (0.0001) | 2.896 |
| New York | -0.145 (0.162) | 0.806 (0.3693) | 0.865 |
| *Clinic-Type Dummies* | | | |
| Family Practice | 0.901 (0.27)*** | 11.118 (0.0009) | 2.462 |
| Primary Care | 0.898 (0.269)*** | 11.163 (0.0008) | 2.454 |
| Internal Medicine | 1.166 (0.303)*** | 14.786 (0.0001) | 3.210 |
| Women's | 0.727 (0.321)** | 5.133 (0.0235) | 2.068 |
| Multi-Specialty | 1.145 (0.286)*** | 15.966 (0.0001) | 3.141 |
| Pediatric | 1.151 (0.286)*** | 16.196 (0.0001) | 3.160 |
| *Clinic Characteristics* | | | |
| No. Physicians | 0.039 (0.021)* | 3.359 (0.0668) | 1.040 |
| Year Opened | 0.018 (0.01)* | 3.646 (0.0562) | 1.019 |
| *Geographic Location Controls* | | | |
| Large City County | 0.439 (0.181)** | 5.878 (0.0153) | 1.550 |
| Large City Metro Area Counties | 0.37 (0.193)* | 3.684 (0.0549) | 1.448 |
| Small City County | -0.207 (0.201) | 1.066 (0.3018) | 0.813 |
| Small City Metro Area Counties | -0.351 (0.296) | 1.406 (0.2358) | 0.704 |
| Rural County | -0.702 (0.313)** | 5.034 (0.0248) | 0.496 |
| | | | |
| Number of Clinics in Sample | 1286 | | |
| Likelihood Ratio (Pr> $\chi^2$) | 172.236 (0.0001) | | |
| Wald (Pr> $\chi^2$) | 167.273 (0.0001) | | |

Notes:

1. The baseline dummies are as follows: (a) State: Illinois; and (b) Clinic-Type: Urgent Care.
2. The asterisks *** represents significance at the 1% level, ** at the 5% level, and * at the 10% level.