

**THE DIFFUSION OF HEALTH INFORMATION TECHNOLOGY IN SMALL
PHYSICIAN PRACTICES: PRACTICE CHARACTERISTICS AND COMPETITION
AS DRIVERS OF ADOPTION**

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**THE DIFFUSION OF HEALTH INFORMATION TECHNOLOGY IN SMALL
PHYSICIAN PRACTICES: PRACTICE CHARACTERISTICS AND COMPETITION
AS DRIVERS OF ADOPTION**

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SUMMARY

This paper considers the adoption of Health Information Technology (HIT) by physician clinics with ten or fewer physicians. The paper considers the theoretical economics literature on technology adoption for a new technology and has a place in the empirical tests of these models. The two major hypotheses tested in the paper are that the probability of adopting HIT increases with the number of physicians working at the clinic and if the clinic is part of a chain of clinics, and that it also increases with increased competition at the market level measured by the number of clinics per 10,000 residents in a county. To test these hypotheses, the paper first estimates a baseline logit model followed by three hazard rate models. In each case, clinic size is found to have positive though not significant effect on the probability of adoption (in the logit model) or to decrease the predicted time to adoption for the clinic (in the hazard rate models), being in a chain of clinics is found to have a strong positive and significant on the probability of adoption, and increased competition is found to have a positive though not significant effect on the probability of adoption.

1. Introduction

During the almost year long debate in 2009 over health care reform in the U.S., many economists and politicians from across the political spectrum made the observation that the U.S. spends much more on health care than other developed countries but does not necessarily have better health outcomes as a result of the extra spending (McKinsey, 2008). In this context, several alternatives have been proposed for limiting health care costs while increasing (or at least not decreasing) the quality of care Americans receive. While many of these proposals have been controversial, one idea that has received positive attention as both a cost reducer and quality improver has been increased use of Health Information Technology (HIT) by the industry. In fact, one study estimated that a nationally standardized HIT system could save the U.S. health care industry \$78 billion dollars per year (Walker, 2005) which would be 3% of total spending on health care.

Next, I briefly describe some characteristics of the U.S. health care industry. Nominal spending on health care has been rising steadily over the past decades; see Figure 1 (Centers for Medicare and Medicaid Services, 2009). Furthermore, since 1960, health care spending has risen from \$147.85 per person to \$8,159 per person in 2009 (Centers for Medicare and Medicaid Services, 2009). Not only has total spending increased dramatically, but also the health care's share of total GDP which increased from 5.2% in 1960 to 17.6% in 2009; see Figure 2 (Centers for Medicare and Medicaid Services, 2009). Figure 3 shows the growth rate of GDP, population, and health care expenditures from 1998 to 2009. Over this time period, population growth has remained steady around 1%, GDP has fluctuated between just over 6% to as low as -1%, but health care spending growth has remained at or above 4% for the entire period and

always above GDP growth. Furthermore, health care expenditures are projected to rise by another 73% over the next ten years (Centers for Medicare and Medicaid Services, 2009).

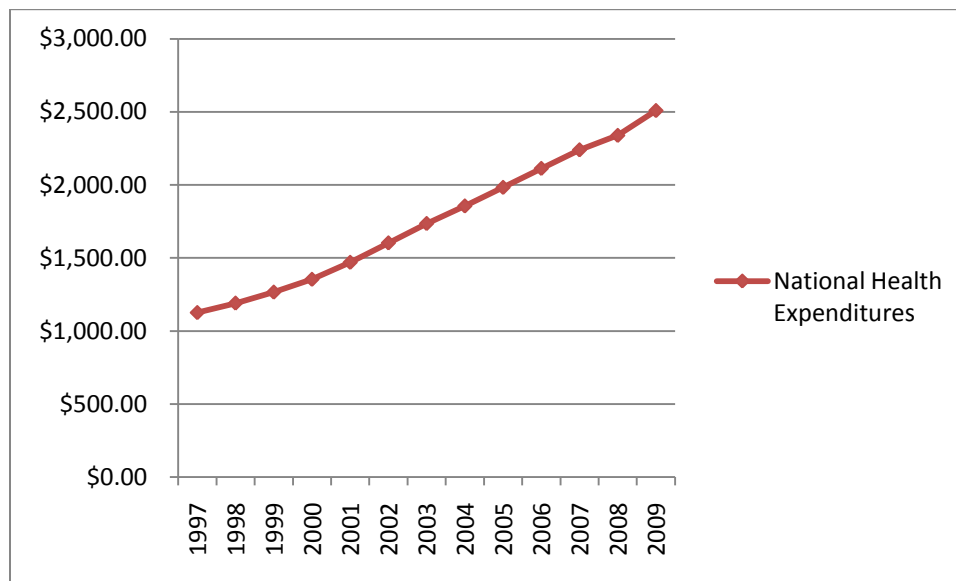


Figure 1. Total National Health Expenditures (in billions) Source: Centers for Medicare and Medicaid Services, 2009.

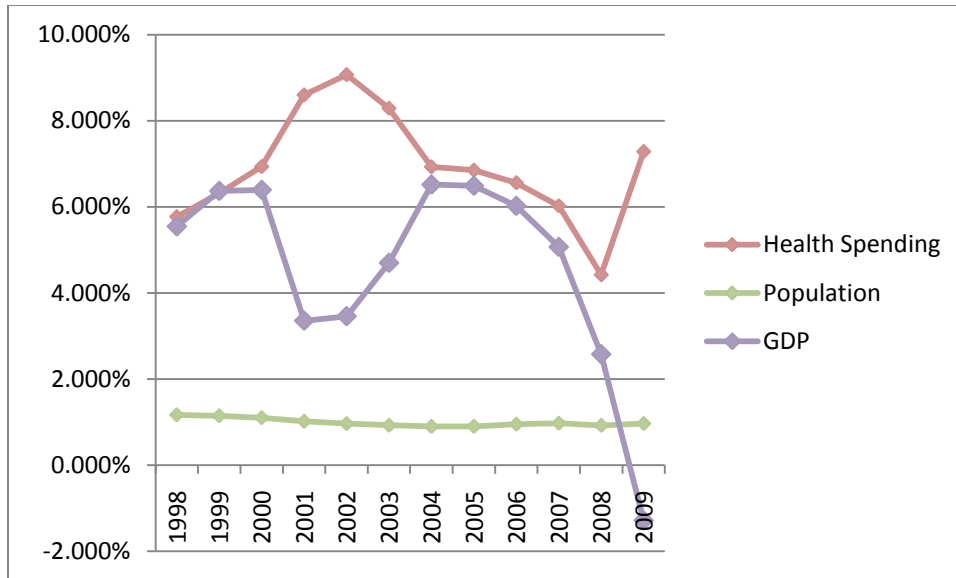


Figure 2. Growth Rates of Health Spending, Population, and GDP. Source: Centers for Medicare and Medicaid Services, 2009

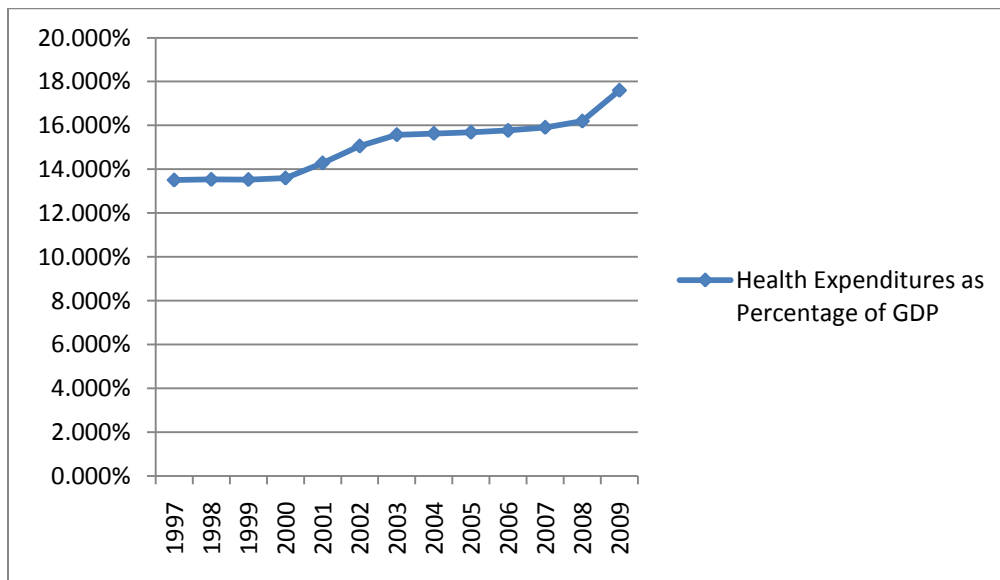


Figure 3. Health Expenditures as Percentage of GDP. Source: Centers for Medicare and Medicaid Services, 2009.

If the benefits were high, one would find the high costs more palatable. However,, U.S. health outcomes do not appear to be better than in other developed countries who spend far less on health care. On the one hand, the top-of-the-line health care in the U.S. is potentially stronger than in other countries, and rich or well-insured patients have access to the best and newest medicines more so than in other countries (McKinsey, 2008). However, the U.S. is behind other developed countries in infant mortality and life expectancy (McKinsey, 2008). The net effect of relatively lesser provision of preventative care and greater provision of high-end care is unclear, and many consider this as a negative feature of the US system as the low preventative care leads to potentially higher incidence of more serious health care problems over an individuals' lifespan. All of this points to a strong need in U.S. health care to find ways to reduce costs of the health care system while trying to maintain or improve quality.

Given that HIT is a way for the health care industry to potentially find large longer-run cost savings from widespread adoption of HIT,¹ it is surprising that HIT adoption is not more prevalent. To date, only 44% of ambulatory care practices have adopted any form of HIT² and far fewer have adopted more advanced systems that are seen as important to obtaining system wide benefits from adoption (CDC/NCHS, 2009); see Figure 4.

¹ In addition to the previously mentioned study by Walker, Hillestad (2005) estimates the savings from full, nationwide adoption of HIT at \$81 billion per year.

² Excluding systems for billing purposes only

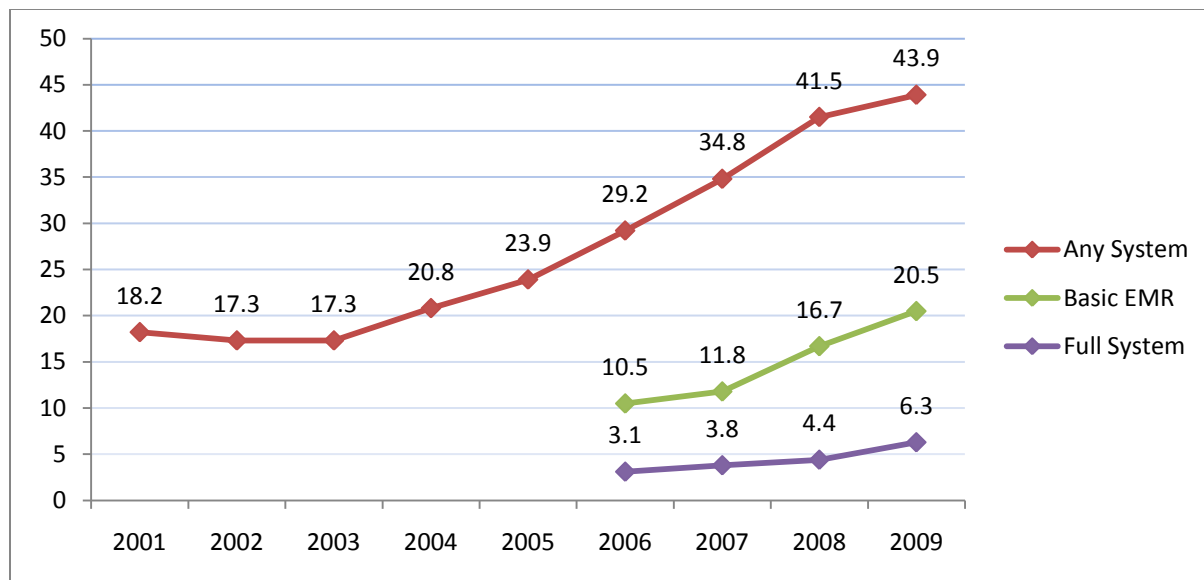


Figure 4. Adoption Rates of HIT Systems by System Capability

Furthermore, compared to other developed countries, the U.S. lags far behind in HIT adoption in physician clinics. In 2006, only 28% of physicians used EMR in their practices in the U.S. compared 98% in the Netherlands, 89% in the U.K., and 42% in Germany; see Figure 5 (Commonwealth Fund, 2008). This may be due to the other countries being more involved in encouraging physicians to adopt HIT which may be very politically difficult for the U.S. to follow potentially due to their nationalized healthcare systems which greatly subsidize many aspects and require various procedures and processes to conform across the whole system. In a more market based approach such as US, it is up to the individual clinics to adopt (Blumenthal, 2007).

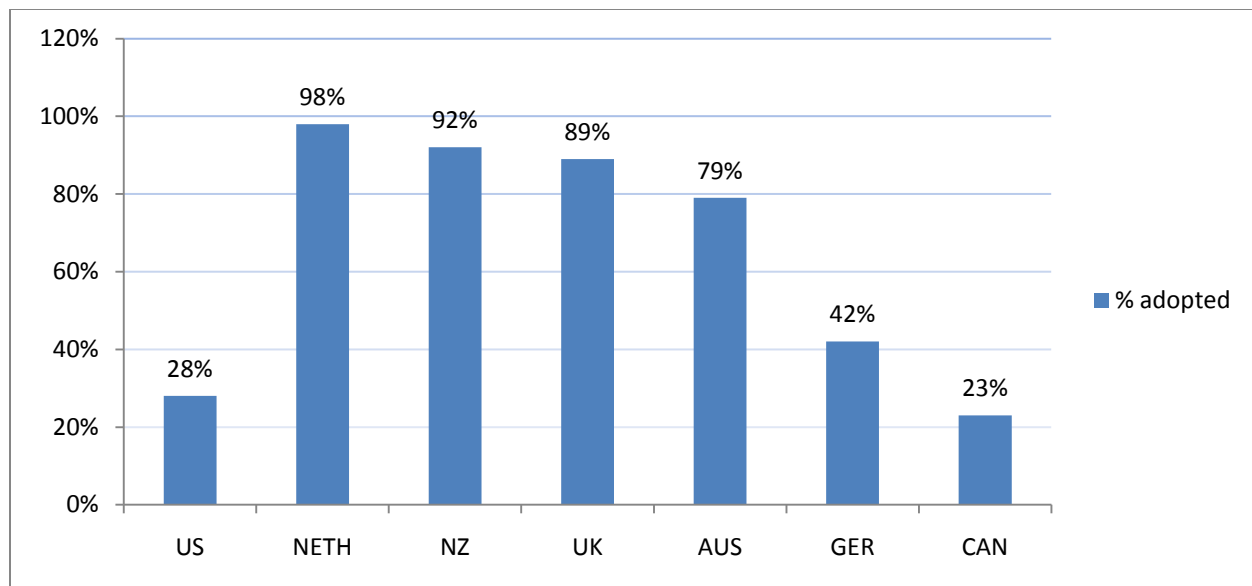


Figure 5. U.S. Physician Clinic HIT Adoption Levels Compared to Other Countries (2006).
Source Commonwealth Fund National Scorecard on U.S. Health System Performance, 2008.

There are many reasons stated for this slow pace of adoption. First, many physicians offices, particularly small offices, find it challenging from a business perspective, even if they believe in its usefulness in the health care system as a whole, to implement HIT. This problem has several aspects. First, many of the benefits of HIT adoption end up going to payers (e.g. insurance companies or government programs) or patients rather than the practice (Hillestad, 2005). For example, if the practice's records enable it to avoid running a duplicate test, the practice may actually lose money on not having the extra work to do, and while this is a net benefit for the health care system as a whole, the outcome for the physician is most likely either neutral or somewhat negative while the benefits go to the payer and patient. Second, an unsuccessful adoption may be devastating to a small practice from a cost perspective. Third, HIT adoption can require a major change in the way the practice operates (Blumenthal, 2007). For instance, it has been estimated that HIT adoption costs a practice \$11,200 per full-time

physician in the first year after adoption in lost productivity due to adjusting to the way the practice operates with HIT (Wang, 2003).

Another reason for the slow diffusion of HIT is that there is currently major uncertainty for physicians concerning the HIT industry (Bower, 2005). This takes several forms. First, we should note that the vast majority of doctors are not Information Technology experts. For those in small practices, if there is no HIT champion for HIT adoption, it may be both challenging and intimidating to select an effective HIT system, and faced with the high costs of an HIT system, small clinics know that a wrong choice could be devastating. The HIT industry has been very dynamic in the past few years.... Furthermore, there has been much talk on creating industry wide standards lately that may make physicians reluctant to adopt a system now that may or may not be compatible with future standards (Bower, 2005).

In the 2009 \$787 billion American Recovery and Reinvestment Act, Congress allotted \$19 billion for promoting the study and use of Health Information Technology (HIT). The stimulus bill calls for the creation of national standards for electronic health records (EHR). In addition, it seeks to eliminate many of the barriers to HIT adoption by authorizing Medicare payments of up to \$44,000 over five years to small clinics who show “meaningful use” of HIT in 2010 where meaningful use includes system capabilities such as the electronic data exchange and ability to report quality measures (Steinbrook, 2009). Failure to adopt HIT and demonstrate “meaningful use” by the end of the five year period will subject clinics to reductions in Medicare reimbursements (Steinbrook, 2009). The Congressional Budget Office projects that these incentives will increase diffusion speed of HIT by increasing the percentage of clinics adopting comprehensive electronic health records by 2019 to 90% from the 65% that would be expected to do so anyway (Sunshine, 2009). In addition, the stimulus bill created an HIT committee on

standards and an HIT committee on policy which specifically focuses on creating interoperable electronic health records allowing different health care entities to more easily communicate patient records with each other (Steinbrook, 2009). Beginning in 2010, the Department of Health and Human Services will begin certifying HIT (Steinbrook, 2009). In the long run, the goal is to have a national system of electronic records. Such a system would allow patients who live in one location and are injured or become sick in another location to be able to go to the hospital or a physician and have their records be easily accessible. Another benefit of a national electronic medical record system is that it would allow for statistical analysis of different treatments and their outcomes so that doctors and researchers are much more easily able to study which treatments are most effective. Since having a higher percentage of clinics who have adopted HIT is a likely prerequisite for such an integrated national system, obtaining a firm understanding of what factors drive HIT adoption is an important task.

The goals of my paper are: (1) to identify some of the characteristics that are likely to influence adoption of HIT by clinics; and (2) estimate their effect. The results will be useful in identifying some of the key drivers of HIT adoption, and policy-relevant in the sense that we can point to areas where stimulus and other government funds and initiatives can be used to impact most directly the adoption of HIT. In this paper, I provide a survey of some of the economic models of technology adoption, and my examination of these models led to the following testable hypotheses that would lead to increased likelihood of HIT adoption: (1) clinic size (defined by the number of physicians); (2) whether or not the clinic is part of a chain of clinics; and (3) the extent of competition from other clinics in the same geographic area.

The econometric analysis finds strong evidence for size effects being important determinants of adoption patterns. It also finds some evidence that competition plays a role in HIT adoption although the result is not conclusive.

2. Literature Review

The Literature Review section is divided into two parts. The first part considers the relevant literature on HIT adoption. The second part of the literature review considers the theoretical and empirical technology adoption literature which allows me to develop several hypotheses concerning HIT adoption that will be examined later in the paper.

2.1 Health Information Technology Adoption Literature

The economics literature on HIT adoption is almost non-existent. The only other paper to consider diffusion of HIT from an economic perspective is Bower (2005). However, instead of considering specific factor influencing HIT adoption, Bower predicts HIT diffusion based on similarity to other technologies. After considering many technologies, Bower finds that HIT is most similar in the characteristics that would drive diffusion to Enterprise Resource Planning (ERP) technology. In this context, Bower concludes that HIT adoption is not actually slow based on its type of technology and the health care industry, but rather is diffusing at a pace similar to ERP.

On the other hand, there has been much research on the benefits of HIT adoption. Generally, there are four areas where HIT can improve the health care system: (1) improved workflow; (2) improved quality of patient care; (3) improved patient safety; and (4) increasing system-wide efficiency. Improved workflow can stem from reducing reliance on paper records which can benefit an individual clinic by improving efficiency and reducing the number of hours of administrative staff (Congressional Budget Office, 2008). In addition, Poissant (2005) reported that nurses spent less time working on documentation after implementing an HIT

system. Also, HIT systems can help reduce the number of duplicate lab tests significantly (Congressional Budget Office, 2008).

HIT can improve quality and patient safety in several ways as well. First, HIT decision support systems can help physicians make better decisions based on patient information and history. In addition, computerized reminders can help patients adhere to their medication schedule more easily (Chaudhry, 2006). Decision support systems can help physicians recognize when there are cheaper, generic alternatives to patented prescription drugs (Congressional Budget Office, 2008). Furthermore, HIT systems can reduce the rate of medication errors and adverse drug events (Hillestad, 2005).

HIT also has the potential to make the health care system more efficient as a whole. As HIT systems fitted with information exchange capabilities become more prominent, many of the same quality improvements and efficiency gains noted above (e.g. less frequent lab test duplication, fewer medical errors, and much reduced information sharing costs) could be gained system wide. Finally, with the additional manageability of large amounts of patient data, it would be much easier for researchers to study the relative effectiveness of different treatments (Congressional Budget Office, 2008).

Despite the enthusiasm and potential of HIT, there are some catches to the potential benefits of HIT adoption. Sidorov (2006) notes that studies on the potential savings such as Hillestad (2005) rely on best case scenarios. Also, the vast majority of savings would go to Medicare and private insurers (Bates, 2005). And the benefits that do go to the physician are most prominent in finding improving efficiency in billing (Sidorov, 2005). For this reason, billing is the most common information technology functionality found in small health clinics. Furthermore, the level of quality improvement is questionable. Schellhase (2003) found that 75%

of physicians sometimes ignored reminders from their HIT system. Poissant (2005) found that clinics that adopted EHR increased physician time spent on documentation by 17%. Together these critiques point out that high levels of HIT adoption alone are not sufficient to get all the potential gains from HIT, but that HIT systems must be used effectively by adopting clinics and be accompanied by process and workflow changes to fully obtain the benefits of an HIT system.

2.1.1 The Business Case for HIT Adoption

There are two main papers which have analyzed HIT adoption from a profit maximizing point of view in small physician clinics: Wang (2003) and Miller (2005). The main result of Wang's paper is that practices which implement fully functional EMR see \$86,400 net profit (includes increased revenues and decreased costs) per physician over a five year period. The benefits are lower and even slightly negative when less than a full system is implemented. Miller finds that it takes clinics 2.5 years to recover their initial investment which is followed by \$33,000 net profit per year. If we convert that measure to Wang's five year window, Miller's study projects a net profit of \$82,500 over five years which is remarkably close to Wang's finding.

Financial Benefits of HIT Adoption

In particular, Wang finds that the majority of the financial benefits from HIT occur in four areas:

- Savings in Drug Expenditures
- Improved Utilization of Radiology Tests
- Better Capture of Charges
- Decreased Billing Errors

Wang further disaggregates the financial benefits of HIT adoption by type of reimbursement mechanism for the physician. Under capitated reimbursement³, HIT is primarily useful in reducing medical usage for the physician (e.g. reducing lab tests and reducing medication errors). Furthermore, 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. Finally, regardless of the reimbursement method, physicians were able to reduce paper chart pulls by an average of 600 per year and reduce transcription costs.

In Miller's study the key financial benefits are \$33,000 per year per physician that results from:

- Decrease in administrative staff hours
- Decrease in transcription costs
- Increased total visits due to reduced physician time per patient
- Increased coding levels for treatments from better documentation of services performed

Furthermore, there were noticeable increases in several quality areas especially in drug related reminders and data organization, accessibility, and legibility.

Financial Costs of HIT

Wang's paper also provides a nice framework for discussing the costs associated with adopting HIT. First, there are several fixed costs for HIT adoption which include the cost of the HIT software and hardware, training the administrative workers and doctors to use the system, and broadly speaking any other implementation costs. These are the direct fixed costs of implementing an HIT system. Another fixed cost is what Wang calls "induced costs." These

³ Capitated Reimbursement is a system where physicians are paid a set amount for each person which assigned to that physician whether or not that person uses medical care for a particular time period

costs are all those involved in switching from a pen and paper system to an HIT system as well as a temporary reduction in overall practice productivity for several months after the system change.

Furthermore, Wang estimates these costs using a combination of data from the Integrated Delivery Network which his study focuses on and expert opinion:

- Software Costs: \$1600 per physician per year
- Implementation Costs: \$3400 per physician per year
- Ongoing Maintenance and Support Costs: \$1500 per physician per year
- Hardware Costs: \$6600 per provider every 3 years
- Temporary Loss of Productivity: \$11,200 in first year

Miller's conducts a case study of fourteen small physician practices who have adopted an EHR system. Miller estimates the initial cost of an EHR system at \$44,000 with ongoing costs of \$8,500 per year. Initial costs are made up on average \$22,000 to buy the software, \$13,000 in hardware costs, and \$7,000 in immediate productivity loss upon switching to EMR. Concerning ongoing costs, 91% of the total come from contracted IT staff, maintenance and support, and hardware replacement.

In addition, Miller notes the risk of adopting EHR. Of the 14 practices in the study, 3 experienced severe problems that were at least partly related to the implementation of the system. In the most extreme case, one clinic had no billing or revenue for ten months and almost went out of business.

There have been several criticisms of Wang's and Miller's papers. First, many of the numbers that Wang gives are particularly troubling for economists. For example, listing software cost as a "by physician" basis does not seem to make much sense. I would expect that

possibly software costs increase as the number of physicians in the practice increases, but surely a two physician firm pays less per physician for an HIT system with same capabilities as a one physician firm. Furthermore, other papers have criticized the likelihood that Wang's paper can be generalized to other practices on the grounds that the main data source utilized a home grown system for his IDN when many physicians are in the position where they must select more of a one-size-fits-all or at least something which is not tailored to their individual practice (Blumenthal, 2007). In Miller's case, the clinics are selected based on which vendor it has purchased an HIT system from. If this particular product has either better or worse financial returns for a practice than another system would have, then Miller's results would be biased one way or the other. Also, there appears to be a great deal of self selection in this type of study. Since HIT adoption is a major risk for a small practice to take, we would expect there to be a positive return on investment, and that those practices which would find it to be the most profitable would be the practices which would adopt. In other words, \$86,400 should be seen more as an upper bound to the profitability of HIT adoption rather than what a practice should expect as a result of HIT adoption.

2.2 Technology Adoption Literature Review

2.2.1 Theoretical Contributions

The seminal technology adoption paper is Griliches (1957) paper on the adoption of hybrid corn by farmers. Griliches recognized two stylized facts about technology adoption that any modern theory of technology adoption must explain. First, technology adoption is a process – that is, it diffuses throughout an industry rather than all firms adopting simultaneously. Second, when considered at the industry level, plotting the proportion of adopters against time

results in an S-shaped diffusion curve. In other words, firms adopt slowly at first, then many firms adopt quickly in the middle, followed by the technology being slowly adopted by the last adopters in the industry.

More modern papers have been classified by Hoppe (2002) into four distinct categories based on their method of explaining the above stylized facts. Hoppe classifies papers on two dimensions: (i) certainty vs. uncertainty and (ii) strategic vs. non-strategic. Where these two dimensions intersect gives rise to Hoppe's four categories.

The first category to consider then is the adoption of a new technology under certainty of its value to the firm and where firm's actions do not affect the payoffs to other firms (i.e. certain and non-strategic). Most of the early technology adoption models fit this description. In these models, the driving force behind technology adoption is characteristics of the firm. The most common characteristic in these models promoting technology adoption is the size of the firm. Later in this paper, I consider in detail Stoneman's (2002) model of technology adoption that fits into this category.

The second category of technology adoption papers retains the assumption that firms know perfectly well the value of adopting a new technology, but relaxes the assumption that there is no strategic interaction between firms. The seminal papers in this area are Reinganum (1981) and Fudenberg (1985). There is much more variation in the models' predictions in this body of literature than in the other categories. Some predict that diffusion speed is increased because of competition (e.g. Gotz), some predict that diffusion speed is slowed by competition, and some predict that diffusion speed is faster for some firms and slower for others (e.g. Reinganum). Furthermore, there are also differences in that some models predict an early-mover advantage (e.g. Reinganum) while others predict a late-mover advantage (e.g. Dutta). Finally,

one other notable paper examines market structure in relation to technology diffusion and predicts that markets where firms are engaged in Cournot competition will have faster diffusion of a new technology than markets where firms are engaged in product differentiated Bertrand competition (Milliou, 2009).

The third class of models that is worth mentioning in relation to HIT adoption is models where the firm faces uncertainty regarding the value of the new technology or the arrival date of a better version of new technology. The seminal work in this area is Jensen's (1982) model where the firm does not know the value of a new technology. At each time period, the firm can either adopt the new technology or wait and learn more about whether or not the technology the technology will actually be profitable. The longer the firm waits, the more accurately it can tell whether or not the technology will be profitable or not; however, this comes at the cost of losing potential profits from adopting a profitable technology. In this model, it is possible for a firm to adopt an unprofitable technology. Diffusion of the new technology occurs either because of different learning mechanisms between firms or different confidence threshold for adopting a new technology. A notable adaptation of Jensen's model is Weiss (1994). In Weiss's model, 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 forthcoming experience delayed adoption. This model is particularly appealing for an HIT adoption paper since two of the primary reasons posited for delayed adoption of HIT are concern about the actual value of HIT for a physician clinic and concerns about improving quality or buying a product that will become obsolete when new standards of HIT emerge. While these models do seem to have

relevance for HIT adoption, there are simply no data available to test these class of models for HIT adoption.

2.2.1 Stoneman's Model: Firm Size Driving Technology Adoption

In Stoneman's book *The Economics of Technological Diffusion* (2002), he presents a model where diffusion occurs as a result of firm characteristics that builds upon the seminal work of Davies (1979) in this area. In this approach, firms with different characteristics receive different benefits from adopting a new technology. Here, I present a slightly modified version of Stoneman's model. Stoneman's model predicts a positive relationship between firm size and probability of adoption. The reason that larger firms are more likely to adopt are economies of scale regarding the use of the new technology and less risk exposure for larger firms. Physician clinics may experience economies of scale from clinic size or being in a chain of clinics in the sense that it may need to employ one IT person and buy software and hardware that does not increase much in price for additional physicians.

First, in Stoneman's model all N firms in an industry know of the existence of a new technology. Firms face the same cost of adopting a new technology. Finally, firms differ by some characteristics which leads to each firm having some different level of benefits that would result from adopting the new technology according to some distribution. In order to decide whether or not to adopt the new technology, the firm compares the benefits of adoption with the cost of adoption. In this case, the firm's profits do not depend on strategic interaction with other firms. This will be discussed in the next model presented in this paper.

In this model, diffusion can result from two mechanisms. First, the cost of adoption could be decreasing over time for the same technology. Second, the benefits from adopting

could be increasing over time (e.g. the quality of the new technology could be improving over time).

Now, I introduce some notation in order to formalize the model. Let $\pi_0(t)$ be the firm's profits at time t when the firm has not adopted the new technology and $\pi_1(t)$ be the firm's profits after adopting a new technology. Since adopting the new technology reduces marginal costs for the firm, we have $\pi_1(t) > \pi_0(t)$. Let $\pi(t) = \pi_1(t) - \pi_0(t) > 0$ be the net increase in profits from adopting the new technology at time t ; and further assume that $\pi(\tau) = \pi(t)$ for all $\tau > t$. That is, the value of the new technology is constant for all time periods after adoption. However, this does not preclude the quality of the technology from improving in the time periods before adoption, so that the firm could get a 'better' technology by waiting to adopt. Then, since profits are constant every period after adoption, the present value of profits by adopting the new technology at time t are given by $V(t) = \frac{\pi(t)}{r}$ where r is the discount rate.

Now, allowing for the profit function to differ across firms by their characteristics, we can write the net profit function as

$$\pi(t, \mathbf{C}(t)) \quad (1)$$

where $\mathbf{C}(t)$ is a vector of firm characteristics that could vary by time period. In order to simplify the model and because most previous works including Davies (1979) have focused on firm size as being the driving firm characteristic, simplify the above equation to be

$$\pi(t, Q) \quad (2)$$

where Q is the size of the firm and assuming the size of the firm is not changing over time. This implies that $V(t, Q) = \frac{\pi(t, Q)}{r}$.

Now, let $P(t)$ be the price of the new technology at time t . Here, the model ignores ongoing costs associated with new technology in order to focus on the initial cost of adopting the new technology. Then, the net present value of adopting the new technology is

$$NPV(t, Q) = V(t, Q) - P(t) = \frac{\pi(t, Q)}{r} - P(t) \quad (3)$$

From the net present value, there are two requirements in order for the firm to adopt the new technology. First, there is what Stoneman terms the “profitability condition.” That is,

$$\pi(t, Q) \geq rP(t) \quad (4)$$

This is a necessary condition in that it requires that present value of increased profits from adopting the new technology exceed the present value of the price of adopting the new technology. The second condition is what Stoneman calls the “arbitrage condition.” This condition is that the firm will adopt when the adoption is most profitable. Specifically, this means that even if the firm satisfies the profitability condition in one period, it may still wait to adopt if it receives a greater benefit in a subsequent period. This could result either from expected increases in the quality of the new technology in the future or from an expected decrease in price in the future. This is a sufficient condition for adopting a new technology. If the firm only considers one period in advance, it can be expressed as

$$\frac{\pi(t, Q)}{r} - P(t) \geq \frac{\frac{E(\pi(t+1, Q))}{r} - E(P(t+1))}{(1+r)} \quad (5)$$

where E indicates the expected value of net profits and price of the new technology in period $t+1$.

Multiplying through by $(1+r)$ and simplifying yields

$$\pi(t, Q) - rP(t) \geq \frac{E(\pi(t+1, Q))}{r} - \frac{\pi(t, Q)}{r} - E(P(t+1)) + P(t) \quad (6)$$

Equation (6)'s interpretation is that firm's will adopt at time t rather than wait if the benefit from adopting at time t , $\frac{\pi(t, Q)}{r} - P(t)$, is greater than the benefit of waiting (i.e. the benefit in present value that comes from generating a higher annual gross profit gain or paying a lower price for the technology at time $t+1$). Also, it is worth noting that the arbitrage condition reduces to the profitability condition if the expectation of net profits and expected value of price of the new technology are equal to the current net profits and price of the new technology, respectively. Finally, with one last adjustment to the above equation we can compare the costs and benefits of adoption.

$$\pi(t, Q) \geq rP(t) + \frac{E(\pi(t+1, Q))}{r} - \frac{\pi(t, Q)}{r} - E(P(t+1)) + P(t) \quad (7)$$

Thus, the left hand side gives the benefits from adopting at time t , while the right hand side gives the costs. This is the condition under which the firm will adopt the new technology.

Finally, Stoneman solves explicitly for the threshold size of the firm will which adopt at a particular time t . Here, I present a slightly modified version of this. Contrary to the above, allow the cost of acquiring the new technology to be dependent on the size of the firm and denoted by $C(t, Q)$ where $\frac{dC}{dQ} > 0$ and $\frac{d^2C}{dQ^2} < 0$. That is, the cost of acquiring the new technology increases with the size of the firm but at a decreasing rate. For simplicity, I'll explicitly express $C(t, Q) = \alpha Q^{\frac{1}{2}}P(t)$ where $P(t)$ is the price level of the new technology. Similarly, define $\pi(t, Q) = A(t)Q$

where $A(t)$ is a time-sensitive function shifting the payoff from adopting the new technology.

Then, using the above condition for adoption and substituting gives

$$A(t)Q \geq r\alpha Q^{\frac{1}{2}}P(t) + A(t+1)\frac{Q}{r} - A(t)\frac{Q}{r} - \alpha Q^{\frac{1}{2}}E[P(t+1)] + \alpha Q^{\frac{1}{2}}P(t) \quad (8)$$

Rearranging the terms, we get the expression

$$\left[A(t) - \frac{A(t+1)}{r} + \frac{A(t)}{r} \right] Q \geq [r\alpha P(t) + \alpha E[P(t+1)] - \alpha P(t)] Q^{\frac{1}{2}} \quad (9)$$

Finally, solving for Q , we get

$$Q \geq \left(\frac{r\alpha P(t) + \alpha E[P(t+1)] - \alpha P(t)}{A(t) - \frac{A(t+1)}{r} + \frac{A(t)}{r}} \right)^2 \quad (10)$$

Thus, if we let $Q^*(t)$ be the value of the right hand side of the above equation, any firm with size $Q > Q^*(t)$ will adopt the new technology at time t . From this expression we can note several comparative statics results:

- For an increased value of α , $Q^*(t)$ increases which means that fewer firms will be users of the technology.
- Since $r < 1$, $Q^*(t)$ is decreasing in $P(t)$ which means that the lower the price at time t , the more likely the firm is to adopt.
- $Q^*(t)$ is increasing in $E[P(t+1)]$. That is, firms which expect a lower price in the next period are less likely to adopt this period.

- $Q^*(t)$ depends on the quality of the technology: $A(t)$ and $A(t+1)$. Since we left the functional forms unspecified above, we cannot say definitively what the relationship is.
- $Q^*(t)$ depends on the discount rate. Again, since we don't know the functional form of $A(t)$ and $A(t+1)$, we cannot say what effect an increase in the discount rate will have on $Q^*(t)$.

Then, the way that diffusion occurs in this model is that over time, the price of the new technology may decrease, the quality of the new technology may increase, and the expectations of future price and future quality may also change. This results in

$$Q^*(t) \leq Q^*(t+1) \leq Q^*(t+2) \leq \dots \quad (11)$$

which means that smaller and smaller firms will adopt at each time period, and the technology will diffuse throughout the industry.

2.2.2 Simplified Gotz's Model: Competition Driving Technology Adoption

A second model to consider in depth is Gotz's model. In contrast to Stoneman's model of a firm's characteristics being the drivers of technology adoption, Gotz's model considers some competitive effects on technology adoption. It is the intellectual descendant of Reinganum's game theoretic model of technology adoption, but Gotz's model has hypotheses which are more straightforward and directly testable. Also in contrast to Reinganum, Gotz's model is based on market competition being modeled as monopolistic competition which is a common strategy for small physician clinic markets (Phelps, 2010).

Below, I present a simplified version of Gotz's model. Gotz's model is based on several key assumptions. First, Gotz models the market that the firms which are considering adopting

the technology as being monopolistically competitive. This means that firms do have some market power emerging from selling a differentiated product. However, there are enough firms so that no one firm's actions affect the payoffs for another firm. Monopolistic competition is a common way to model competition between physician practices (Phelps, 2010). Another of the model's assumptions is that the price of the new technology is dropping over time. There is very little price data for HIT systems in general especially at the detailed level that would be preferred for this type of work; however, it seems reasonable at least that this assumption is valid for the HIT market. The model makes a key prediction which is pertinent for HIT adoption: increased competition will lead to faster diffusion.

The model is developed as follows. There are n firms in a market selling differentiated products. Each firm produces a single product, but some characteristics of the product that one firm produces are different from the characteristics that another firm produces. In the case of the physician practice, each practice is producing health care services, but the service may be differentiated by things such as willingness to accept certain types of insurance, practice location, waiting times, or even friendliness of the physician.

Let the demand for a given firm j be given by

$$Y_j(t) = \frac{p_j(t)^{1/(\alpha-1)}}{\sum_{i=1}^n p_i(t)^{\alpha/(\alpha-1)}} E \quad (1)$$

where $Y_j(t)$ is the residual demand function for firm j at time t , $p_j(t)$ is the price that firm j charges for its differentiated product at time t , α is a parameter between 0 and 1, and E is the

total amount spent by consumers on the differentiated product and indicates the level of demand for the entire market.

Dixit/Stiglitz (1977) show that given this demand function, the elasticity of demand is $\sigma = \frac{1}{1-\alpha}$. Furthermore, since the profit maximizing condition is *Marginal Revenue* = *Marginal Cost*, we have

$$p \left(1 - \frac{1}{\sigma}\right) = c \quad (2)$$

Substituting for σ and solving for p, we get the mark-up pricing rule

$$p = \frac{c}{\alpha} \quad (3)$$

Firms using the original technology (i.e. paper medical records), produce with constant marginal cost \bar{c} . After adoption, the marginal cost is \hat{c} where $\bar{c} > \hat{c} > 0$. Let X be the opportunity cost of purchasing the new technology at time T. The function $X(T)$ is assumed to be decreasing and convex in T so that $X'(T) < 0$ and $X''(T) > 0$. Also, let $X(0) = \infty$ and $X(\infty) = 0$. With this setup, earlier adoption is more expensive, and eventually all firms adopt.

Let π be the operating profits of a given firm. Because of the above mentioned pricing rule, the price a firm charges depends only on whether or not the firm has adopted the new technology. The adoption decision determines the level of marginal cost. And the only way the actions of rival firms enter the firm's profit function via the price index (the denominator of (1)).

Note also that when a fraction q of the n firms have adopted the new technology, the price index can be expressed as follows by substituting the pricing rule (3) into the price index.

$$\sum_{i=1}^n p_i(t)^{\alpha/(\alpha-1)} = (\alpha^{\frac{\alpha}{1-\alpha}}) n \left[q \left(\hat{c}^{\frac{\alpha}{\alpha-1}} - \bar{c}^{\frac{\alpha}{\alpha-1}} \right) + \bar{c}^{\frac{\alpha}{\alpha-1}} \right] \quad (4)$$

Then, there are two types of firms: those who have adopted the new technology at some time t and those which have not yet adopted the new technology. Let $\pi_0^{q(t)}$ denote the payoffs to the firms who have not adopted yet where $q(t)$ is the proportion of firms who have adopted at time t , and let $\pi_1^{q(t)}$ be the payoff to the firms who have adopted at time t . The payoffs can then be expressed as:

$$\pi_0^{q(t)} = (1 - \alpha) \frac{\bar{c}^{\frac{\alpha}{\alpha-1}}}{q(t) \left(\hat{c}^{\frac{\alpha}{\alpha-1}} - \bar{c}^{\frac{\alpha}{\alpha-1}} \right) + \bar{c}^{\frac{\alpha}{\alpha-1}}} \frac{E}{n} \quad (5)$$

$$\pi_1^{q(t)} = (1 - \alpha) \frac{\hat{c}^{\frac{\alpha}{\alpha-1}}}{q(t) \left(\hat{c}^{\frac{\alpha}{\alpha-1}} - \bar{c}^{\frac{\alpha}{\alpha-1}} \right) + \bar{c}^{\frac{\alpha}{\alpha-1}}} \frac{E}{n} \quad (6)$$

Then, each firm will maximize the discounted value of total profits by choosing adoption date T .

The problem is then given by:

$$\max_T \pi(T) = \int_0^T e^{-rt} \pi_0^{q(t)} dt + \int_T^\infty e^{-rt} \pi_1^{q(t)} dt - X(T) \quad (7)$$

First Order Condition:

$$\frac{d\pi(T)}{dT} = e^{-rT} \left(\pi_0^{q(T)} - \pi_1^{q(T)} \right) - X'(T) = 0 \quad (8)$$

For concavity, assume that $\frac{d^2\pi}{dT^2} = re^{-rt} (\pi_0^{q(t)} - \pi_1^{q(t)}) - X''(T) < 0$

Substituting (5) and (6) into (8), we get

$$\frac{d\pi(T)}{dT} = e^{-rt} \left((1 - \alpha) \frac{\bar{c}^{\frac{\alpha}{\alpha-1}} - \hat{c}^{\frac{\alpha}{\alpha-1}}}{q(T) (\hat{c}^{\frac{\alpha}{\alpha-1}} - \bar{c}^{\frac{\alpha}{\alpha-1}}) + \bar{c}^{\frac{\alpha}{\alpha-1}}} \frac{E}{n} \right) - X'(T) = 0 \quad (9)$$

Now, we can use (9) to solve for $q(t)$

$$q(t) = \frac{-e^{-rt} (1 - \alpha) E}{X'(t)} \frac{1}{n} - \frac{\bar{c}^{\frac{\alpha}{\alpha-1}}}{\hat{c}^{\frac{\alpha}{\alpha-1}} - \bar{c}^{\frac{\alpha}{\alpha-1}}} \quad (10)$$

where $q(t)$ is the proportion of firms which have adopted the new technology at any time t .

Finally, we consider some comparative statics of Gotz's model. First, note that higher values of $q(t)$ indicate faster diffusion of the new technology since it indicates a higher proportion of firms which have adopted the new technology at the some point in time. In particular, we are interested in the competition effects predicted by the model.

- E : If the level of residual demand for the differentiated product the firm is producing increases, holding everything else constant, then the proportion of firms which have adopted at any point in time will increase
- n : As the number of firms in the market increases, holding everything else constant, then the proportion of firms which have adopted at any point in time will decrease
- $\frac{n}{E}$: This term is the number of firms in the market normalized by the level of demand in the market and is a proxy for the level of competition in the market. Later, this variable will be proxied by the number of clinics per 10,000 residents in a county. As this level of competition in the market increases, holding everything else constant, then the proportion of firms which have adopted at any point in time will increase

- $\bar{c}^{\frac{\alpha}{\alpha-1}} - \hat{c}^{\frac{\alpha}{\alpha-1}}$: This term is the difference in marginal cost reduction between the old technology and the new technology. If this difference increases, holding everything else constant, then the proportion of firms which have adopted at any point in time will increase

2.2.3 Empirical Papers of Technology Adoption

One of the main issues in the technology adoption literature is that there is a large gap between what types of models are being produced on the theoretical side and the ability of empirical papers to successfully adapt these models into econometric models that can test the theoretical predictions. Below, I give an overview of empirical papers in the technology adoption literature.

There have been quite a few empirical studies of technology adoption for other industries that examine many of the same hypotheses being addressed in this paper. The first wave of technology adoption papers deal with diffusion at an aggregate level. That is, in these papers, the dependent variable is the proportion of adopters of a new technology. The first modern technology adoption paper is Griliches (1957) which modeled farmer's adoption of hybrid seed corn based on differences in the profitability of using the new type of seed. His methodology follows a two-stage process. First, a logistic curve is fitted to the data on the proportion of adopters, but multiple logistic curves are fitted for different groups (in Griliches's case, farmers are grouped by state that their farm is in). Second, he uses a linear regression 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.

More research soon followed using similar methodology to Griliches but testing more hypotheses of technology adoption. Mansfield (1968 and 1977) studied fourteen innovations in four industries found that the most consistent predictor of more rapid technology diffusion was firm size while other factors were only important significant in some instances. Davies (1979) examined twenty-two innovations in UK after World War II. His findings were consistent with Mansfield's that firm size was most important in determining diffusion rates.

After Davies (1979), most work in technology adoption is disaggregated in the sense that the dependent variable is the time of adoption of the new technology. With this change, many of the papers began using Survival Analysis models.

Regarding firm size, Hannan and McDowell (1984) study ATM adoption by banks. They use an exponential hazard rate model. They find evidence that large banks and banks facing higher wage rates will all be more likely to implement ATMs. 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 significant 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 that in some cases 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 market competition, Hannan and McDowell (1984) find that banks operating in more concentrated markets are more likely to implement ATMs. On the other hand, 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) apply a detailed empirical model to test firm characteristic effects, competition effects, and epidemic 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. For a more thorough treatment of many of the important papers (both theoretical and empirical), see Bautista (1999).

From these papers, we see that there is much evidence of a positive effect of firm size on technology adoption in a wide variety of industries. There is also some evidence that competitive forces increase the likelihood of a firm adopting a new technology although the relationship is not as clear. In the next sections, I test the effect of these two factors regarding adoption of HIT in small physician clinics.

3. Methodology

3.1 Logit Model

Logistic regression is one of the most prominent methods for estimating statistical models in which the dependent variable has a finite number of outcomes. It was developed primarily in response to inadequacies of the linear probability model such as the potential for nonsensical predicted probabilities of less than 0 or more than 1, constant marginal effect, and several other statistical issues. The logit specification solves all of these issues and gives rise to an S-shaped relationship between the probability of an event and the explanatory variables.

The most important problem with the linear probability model is that probabilities range from 0 to 1 while a linear specification gives rise to a range from $-\infty$ to $+\infty$. Thus, in order to overcome this, the logit model is derived as follows. First, let $\Pr(y = 1|x)$ be the probability of an event where y is a binary outcome variable equal to 0 if the event did not occur and 1 if the event did occur and x is a vector of explanatory variables. Then, transform the probability of an event into the odds of an event

$$\frac{\Pr(y = 1|x)}{\Pr(y = 0|x)} = \frac{\Pr(y = 1|x)}{1 - \Pr(y = 1|x)} \quad (1)$$

Since $\Pr(y = 1|x) \in [0,1]$, the odds range from 0 to ∞ . Then, taking the log of the odds, we have the expression

$$\ln \left(\frac{\Pr(y = 1|x)}{1 - \Pr(y = 1|x)} \right) \quad (2)$$

This is known as the logit and can range from $-\infty$ to $+\infty$. Now, we can naturally specify a probability model that is linear in the logit

$$\ln\left(\frac{Pr(y = 1|x)}{1 - Pr(y = 1|x)}\right) = x\beta \quad (3)$$

where x is a vector of explanatory variables and β is a vector of parameters.

Finally, from the above specification, it is easy to derive the probability of an event.

Exponentiating both sides gives

$$\frac{Pr(y = 1|x)}{1 - Pr(y = 1|x)} = e^{x\beta} \quad (4)$$

Now, solving for $Pr(y = 1|x)$, we get

$$Pr(y = 1|x) = \frac{e^{x\beta}}{1 + e^{x\beta}} \quad (5)$$

For further discussion on the logit model see Long (1997).

3.2 Survival Analysis Model

A more sophisticated approach to empirically modeling HIT adoption is survival analysis. Survival analysis is a class of statistical methods for studying the occurrence and timing of a discrete event which gets its name from its original use in studying the occurrence of deaths. Karshenas and Stoneman (1993) proposes survival analysis as a way of empirically testing many of the hypotheses derived from theoretical models of technology adoption, and it 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 Stonman (1993).

In order to perform survival analysis, there are several data requirements. First, there must be a discrete change from one state to another that is being modeled. In this case, the state change is from a physician practice not having HIT to having HIT. The other requirement is that the date when the event occurs must also be known.

In many ways, survival analysis is similar to simple linear regression models. However, survival analysis is built to handle two things that a simpler model could not. First, and most importantly, survival analysis is built to handle censoring of data. Censoring occurs when the date of the event has not occurred yet. In our case, any firm which has not adopted HIT yet is a censored observation. Also, survival analysis can generally handle time dependent covariates. For instance, if the number of physicians in the practice changes over time, this can be included in some flavors of survival analysis models.

Similarly to the logit model discussed above, a survival analysis model is probabilistic. That is the time that the event (adoption of HIT) occurs T is a random variable having some probability distribution. The survival function is the probability that an individual survives greater than some point in time t is given by

$$S(t) = \Pr(T > t) = 1 - F(t) \quad (1)$$

where $F(t)$ is the cumulative distribution function. Also, $S(0) = 1$ and $S(\infty) = 0$. This means that no one is “at risk” before time 0 and everyone has “failed” as time goes to infinity. Now, we also need to define the hazard function. This is the instantaneous risk that an event will occur at time t . It is given by

$$h(t) = \lim_{\Delta t \rightarrow 0} \frac{\Pr(t \leq T < t + \Delta t \mid T \geq t)}{\Delta t} \quad (2)$$

This is the probability that the event T occurs in some very small range of times (t to $t + \Delta t$) conditional on the event not having occurred by time t and scaled by the length of time being considered.

Interpreting the hazard rate can be a bit confusing since it is not directly interpretable as a probability since a small denominator above could give it a value over 1. Allison (1995) gives the example of a hazard rate = 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 $12 \times 0.015 = 0.18$ times in a year. One other way to interpret the hazard rate is that $\frac{1}{h(t)}$ gives the expected length of time before the event occurs. So in the above example, the individual would expect to catch the flu once every 5.55 years.

One complication that with survival analysis that is notable for this 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. I use the first year that a clinic adopted HIT although this 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 the empirical results section are, if anything, too small.

3.2.1 Accelerated Failure Time Models

Now that there is a good understanding of the class of models being discussed, I will discuss two subclasses of survival analysis models and then three particular models that will be used in the paper. First, there is the parametric class of models called Accelerated Failure Time models. The idea here is that, in terms of survival, what makes an individual different from another individual is how fast each ages (that is, become more likely to “fail”). In this way, we get a relationship between the survivor functions of any two individuals

$$S_i(t) = S_j(\phi_{ij} t) \quad (3)$$

where ϕ_{ij} is a constant that is specific to the pair (i,j). As an example, Allison (1995) considers the way that dogs and humans age. In this case, the above equation could be written as $S_i(t) = S_j(7t)$ where in this case i is the dog and j is the human. This means that the probability that the dog is still alive after say x years is equal to the probability that the human is still alive after 7x years.

The AFT model is given by

$$T_i = \exp(\beta_0 + \beta_1 x_{i1} + \dots + \beta_k x_{ik} + \sigma \varepsilon_i) \quad (4)$$

However, the AFT model is different from OLS in that it can handle observations where T_i is censored. If it were the case that there were no censored observations in the sample, the estimated coefficients in this model would be the same as in OLS.

There are several different models that are results of the above AFT specification. These models depend on the distributional assumption made about the ε_i s. We consider two different distributional assumptions here although more are possible. First, if the ε_i s are independently and identically distributed extreme value with mean 0 and variance 1, this gives rise to the T_i s

being distributed exponentially. The implication of the T_i s being distributed exponentially is that the specification of the model will require that the hazard rate is constant across time. There is a statistical test to see whether or not this specification is then justified. The second type of AFT model to be considered is when the ε_i s are assumed to be distributed according to a Gumbel distribution. This then leads to the T_i s following a Weibull distribution. The advantage of the Weibull distribution is that it allows for the hazard rate to change over time. In this case, the σ parameter will be estimated and can be interpreted. If $\sigma > 1$, the hazard rate is decreasing over time. If $0.5 < \sigma < 1$, the hazard rate is increasing over time but at a decreasing rate. And if $\sigma < 0.5$, then the hazard rate is increasing at an increasing rate.

3.2.1 Cox (Proportional Hazard) Model

Finally, the last type of survival analysis model is the Cox regression. The Cox regression is different from the AFT models discussed earlier because it is semi-parametric. This means that the researcher no longer must select some type of distribution for the model. The hazard rate for the Cox regression model is given by

$$h_i(t) = \lambda_0(t) \exp(\beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik}) \quad (5)$$

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 log of the above model, we get

$$\log h_i(t) = \alpha(t) + \beta_0 + \beta_1 x_{i1} + \cdots + \beta_k x_{ik} \quad (6)$$

where $\alpha(t) = \log \lambda_0(t)$. Notice that if we specified a functional form such as $\alpha(t) = \alpha$ or $\alpha(t) = \alpha \log t$, then we would have the exponential distribution or Weibull distribution,

respectively which are mentioned above; however, in this case, we are going to leave the functional form unspecified. Instead, if we take the ratio for two individuals i and j , we have

$$\frac{h_i(t)}{h_j(t)} = \exp(\beta_1(x_{i1} - x_{j1}) + \dots + \beta_k(x_{ik} - x_{jk})) \quad (7)$$

so that $\lambda_0(t)$ cancels out. This form requires that the hazard rate for different individuals is proportional over time, and, thus, that the hazard functions should be parallel, but that they can have any shape. The Cox regression was a major advance in statistics and is the most commonly used method in empirical technology adoption papers.

4. Data

The most important data source for this paper is the HIMSS foundation database on technology adoption. Their most recent database is from 2006. It contains information 32,911 health care entities. Of these, there 19,714 ambulatory care practices, 5082 hospitals, 3017 sub-acute practices, as well as data for several other types of health care entities. Among the 19,714 ambulatory care practices, there are 283 different categories although many of them are small and very specific. Out of these categories, seven were selected for consideration in this paper:

- Family Care Clinics
- Primary Care Clinics
- Internal Medicine Clinics
- Multi-Specialty Clinics
- Pediatric Clinics
- Urgent Care Clinics
- Women's Clinics

The data set was then further limited to practices with ten or fewer physicians in order to maintain focus on small clinics and then to the states of Georgia, Florida, and Texas in order to get a manageably sized data set. After placing these constraints on the data, there were 661 clinics remaining. For each clinic, the data set contained data adoption status for several different types of HIT: Electronic Medical Records (EMR), Computerized Physician Order Entry, and Doc Chart. EMR adoption was chosen to measure HIT adoption. The adoption status could be in one of five states: live and operational, installation in progress, contracted/not yet installed, to be replaced, and not automated. For 661 observations in the dataset, all clinics

which had a “to be replaced” status also had a “contracted/not yet installed status.” From the adoption status, I created a binary variable ADOPTER set equal to 1 for all clinics not in the “not automated” category and equal to 0 otherwise. The HIMSS database also contained the year that the clinic adopted EMR for those clinics that had adopted. Furthermore, I collected the number of physicians at the clinic, the ownership status of the clinic (owned, managed, or leased), and the location of the practice. I imputed the INCHAIN variable primarily from a careful examination of the data and internet searches. From the location of the practice, I also gathered data on the number of other practices in the same county in 2009 (County Health Rankings, 2010), the 2006 median income in the county (U.S. Census Bureau, 2006), and the 2006 county population estimate (U.S. Census Bureau 2006 Population Estimates).

Summary statistics for the data are given in Table 1. From Table 1, the average number of physicians in the clinic is low at 3.11. More noticeably, the percentage of firms which have adopted EMR is 51% which means that adopters are somewhat over-represented in our sample.

Table 1 Summary Statistics

Variable	N	Mean	Std Dev	Minimum	Maximum
ADOPTER	661	0.51	.	0	1
INCHAIN	661	0.46	.	0	1
YEAR OPENED	661	1996.03	5.57	1964	2006
PRACTICES PER 10000s	661	10.22	4.57	0	27
COUNTY MEDIAN INCOME 1000s	661	44.85	9.25	22.39	83.49
NUMBER OF PHYSICIANS	661	3.11	2.27	1	10

The statistics for the different types of practices are given in Table 2. Table 2 indicates that there is wide variation in the number of clinics of each type that show up in the data set. More importantly, some types are more likely to be adopters of EMR (e.g. Multi-specialty clinics) while others are less likely (e.g Urgent Care clinics).

Table 2 Practice Type Dummy Variables with EMR adoption statistics

Variable	Count	% of Total	Adopters	% of Type
FAMILY PRACTICE DUMMY	211	31.9%	110	52.1%
PRIMARY CARE DUMMY	138	20.9%	64	46.4%
INTERNAL MEDICINE DUMMY	39	5.9%	25	64.1%
MULTI-SPECIALTY DUMMY	69	10.4%	47	68.1%
PEDIATRIC DUMMY	86	13.0%	55	64.0%
URGENT CARE DUMMY	78	11.8%	21	26.9%
WOMEN DUMMY	40	6.1%	18	45.0%
TOTAL	661	100%	340	51.4%

In order to get a first glimpse at the effects of several of the variables that we have on adopting EMR, below are several graphs that categorize the data and give the percentage of firms adopting in each category. This gives us an opportunity to informally understand what is going on with the data.

Figure 6 shows that clinics in the data set are much more likely to have adopted EMR if they are in a chain of clinics rather than run independently.

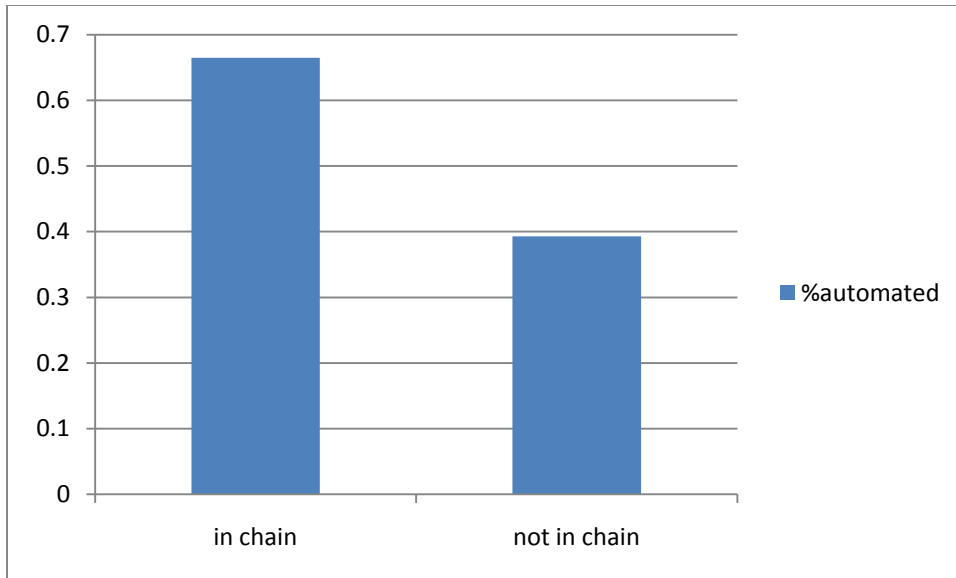


Figure 6. Percentage of firms adopting by INCHAIN status

Figure 7 shows an increasing likelihood of having adopted EMR as the size of the practice increases especially for clinics not in a chain and to some extent for those in a chain. For each practice size, there is an extreme difference between those that are in a chain and those that are not.

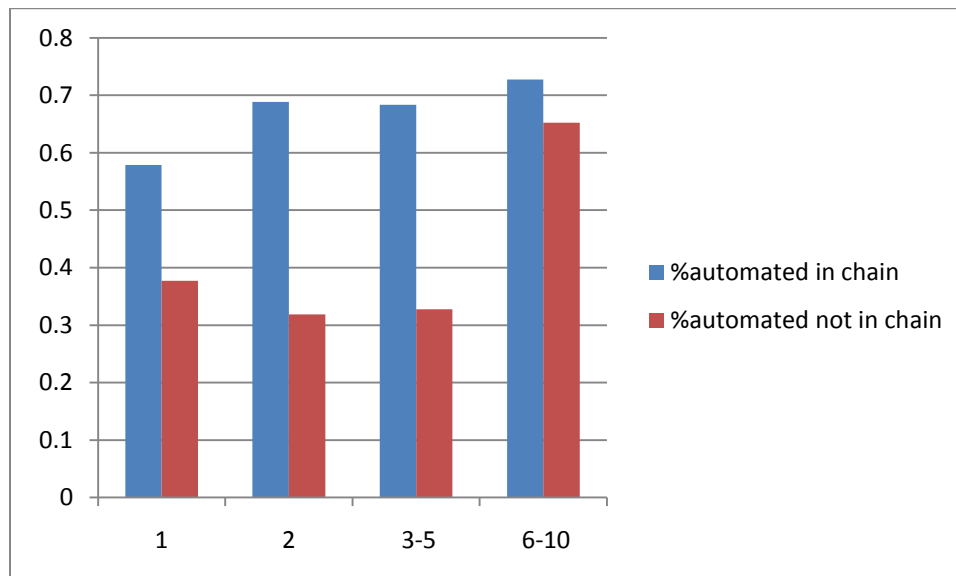


Figure 7. Percentage of firms adopting by firm size and INCHAIN status

Figure 8 graphically illustrates what we saw in Table 2 that there is much variation in the likelihood of adoption across different practice types.

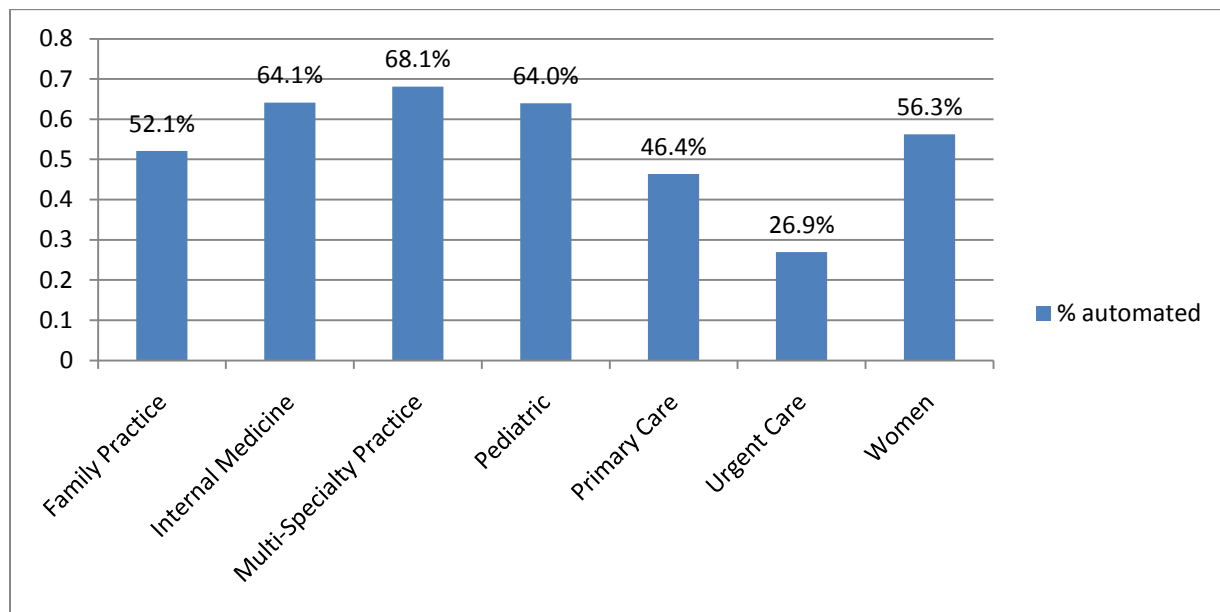


Figure 8. Percentage of firms adopting by practice type

Figure 9 shows what may be a trend of older clinics being more likely adopters of HIT than younger clinics.

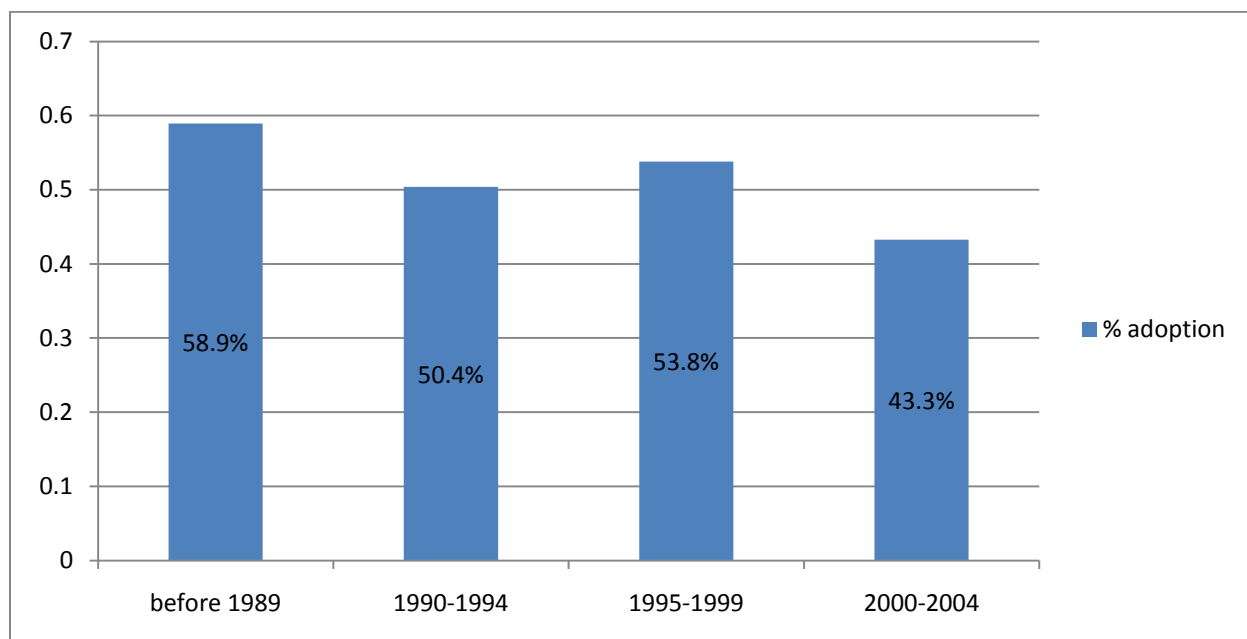


Figure 9. Percentage of firm adopting by year that the practice opened

5. Results

The key variables in the model corresponding to the hypotheses mentioned in the technology adoption literature are INCHAIN, NUMBER OF PHYSICIANS, and PRACTICES PER 10,000. Both the INCHAIN and NUMBER OF PHYSICIANS variables relate to the size of the firm as in Stoneman's Rank model above. PRACTICES PER 10,000 is a measure of competition for the clinic in question as in the Gotz model above. Specifically, we have two hypotheses from the technology adoption literature to test:

- 1) Clinic size (both in terms in number of physicians and whether or not the clinic is a member of a chain of clinics) will be positively related to the probability of having adopted HIT
- 2) PRACTICES PER 10,000 as a proxy for competition that the firm is facing will be positively related to the probability of a clinic adopting HIT.

5.1 Logit Results

The results of the logit model are given in Table 3. This will serve as a baseline model for the more complicated models estimated later in the paper.

Table 3. Logit Model Results

Parameter	DF	Estimate (Standard Error)	Wald Chi- Square	Pr > ChiSq
INTERCEPT	1	48.1932 (31.8647)	2.2875	0.1304
INCHAIN	1	2.0323 (0.9361)	4.7127	0.0299
YEAR OPENED	1	-0.0254 (0.0159)	2.5399	0.111
PRACTICES PER 10000	1	0.00201 (0.00225)	0.8027	0.3703
INCHAIN*PRACTICES PER 10000	1	-0.00024 (0.00401)	0.0034	0.9532
COUNTY MEDIAN INCOME (1000s)	1	0.0383 (0.0139)	7.6463	0.0057
INCHAIN*COUNTY MEDIAN INCOME(1000s)	1	-0.0179 (0.0194)	0.8596	0.3538
NUMBER OF PHYSICIANS	1	0.0643 (0.0573)	1.2606	0.2615
INCHAIN*NUMBER OF PHYSICIANS	1	-0.0224 (0.0784)	0.0813	0.7755
INTERNAL MEDICINE DUMMY	1	0.3056 (0.3877)	0.6213	0.4306
MULTI-SPECIALTY DUMMY	1	0.3896 (0.3303)	1.3917	0.2381
PEDIATRIC DUMMY	1	0.3025 (0.2862)	1.117	0.2906
PRIMARY CARE DUMMY	1	-0.0387 (0.2499)	0.0239	0.8771
URGENT CARE DUMMY	1	-1.2712 (0.3128)	16.5184	<.0001
WOMEN'S CLINIC DUMMY	1	-0.3863 (0.3693)	1.0942	0.2955

Recall that the logit model estimates which factors are important in determining whether or not a clinic has adopted HIT. Concerning the first hypothesis, we find that both INCHAIN

and NUMBER OF PHYSICIANS are positively related to the probability that a firm will adopt an EMR system. Of the two, only INCHAIN is significant at the 5% level. Since INCHAIN is a dummy variable, we can interpret its effect on the odds of adopting EMR. Taking $e^{2.0323} = 7.63$. This means that clinics that are in a chain are over seven times more likely to adopt than those which are not holding other factors constant. If we use the point estimate for NUMBER OF PHYSICIANS, we can interpret as the percentage change in the odds ratio by increasing the number of doctors at the practice by one by computing $100[e^{0.0631} - 1] = 6.64$. This means that for every increase of one doctor at a clinic which is not in a chain, the odds of the clinic having adopting EMR are increased by 6.64% holding all other variables constant.

Concerning the second hypothesis, we find that the sign is again consistent with the hypothesis, but that it is not significant. Interpreting the coefficient for PRACTICES PER 10,000 in the same manner as NUMBER OF PHYSICIANS, we find $100[e^{0.0215} - 1] = 2.03$. This means that for every increase one unit in physician per 10,000 persons, the odds of adopting EMR increase by 2.03%. Recalling from the summary statistics that the mean PRACTICES PER 10,000 is 10.22 and one standard deviation is 4.57, if the PRACTICES PER 10,000s increases by one standard deviation, the model predicts that there will be a $100[e^{0.0215 \times 4.57} - 1] = 10.32\%$ change in the odds of adopting EMR.

Besides the two major hypotheses, there are several other interesting variables that seem to play an interesting role in determining EMR adoption. First, YEAR OPENED has a significant negative effect on adoption. This means that older clinics are more likely to have adopted EMR than more recently opened clinics. This could be due to more stability or a better financial situation for older clinics although we simply do not have enough data to fully understand this. Second, COUNTY MEDIAN INCOME is significant and positively related to

EMR adoption probability. This is in line with our expectations although not a key hypothesis in the technology adoption except in the sense that it could be related to higher levels of demand that at other ceteris paribus clinics. Finally, one of the dummy variable for clinic type is significant. It is the URGENT CARE DUMMY and is in relation to family practices and has a negative effect on EMR adoption probability. This also makes intuitive sense because urgent care facilities are probably less likely to see repeat patients than the other types of clinics which would seem to point to EMR being less important.

In order to get a better understanding of the meaning of some of the important parameters in the model and a sense of the sensitivity of the results to changes in these parameters, Table (3) gives the summary statistics for the predicted probabilities of each observation in the data set, and Table 4 contains the predicted probability of having adopted EMR for eight different types of clinics. The types are created by varying three parameters in the model: INCHAIN, NUMBER OF PHYSICIANS, and PRACTICES PER 10,000s. For “Small” clinic size, NUMBER OF PHYSICIANS = 1; for “Large” clinic size, NUMBER OF PHYSICIANS = 10. For “Low” level of market competition, PRACTICES PER 10,000s = 1; for “High” level of market competition, PRACTICES PER 10,000s = 30. The other variables in the model are held close to their mean: YEAR OPENED = 1996, COUNTY MEDIAN INCOME (1000s) = 45, and the type of practice is FAMILY PRACTICE.

Table 4. Summary Statistics for Predicted Probabilities for Each Observation in Data Set

Variable	N	Mean	Std Dev	Minimum	Maximum
Predicted Probability	661	0.5143722	0.1932699	0.0762028	0.8921101

Table 5. Sensitivity of Logit Results to Changes in Main Explanatory Variables

Clinic Size	In Chain Status	Level of Market Competition	Predicted Probability of Adoption
Small	Not in Chain	Low	32.80%
Small	Not in Chain	High	42.18%
Small	In Chain	Low	61.94%
Small	In Chain	High	69.87%
Large	Not in Chain	Low	46.54%
Large	Not in Chain	High	56.54%
Large	In Chain	Low	70.35%
Large	In Chain	High	77.17%

There are several interesting results from the sensitivity analysis. First, the predicted probabilities range from 32.8% (Small, Not in Chain, Low Competition) to 77.2%(Large, In Chain, High Level of Competition) for a difference of 44.6% between the most likely and least likely types of clinics to adopt based on the key explanatory variables in the model. However, this is a quite a bit smaller than the difference between the maximum and minimum predicted probabilities for all observations in the data set as seen in Table 3. This discrepancy is a result of significant factors such as YEAR OPENED, and COUNTY MEDIAN INCOME not varying at all in the results in Table 4. Furthermore, in Table 5, the four largest predicted probabilities all go to clinics which are IN CHAIN. Among these, the being a large clinic and facing a high level of competition both have positive and similar magnitude effects.

5.2 Survival Analysis Results

Next, we consider the survival analysis models. Figure 10 plots the Survival function against time. The labeling of time is the duration since clinics first became “at risk” of adopting. For each clinic, the first time “at risk” is set as 1996 which is the first year that a clinic adopted in the sample.

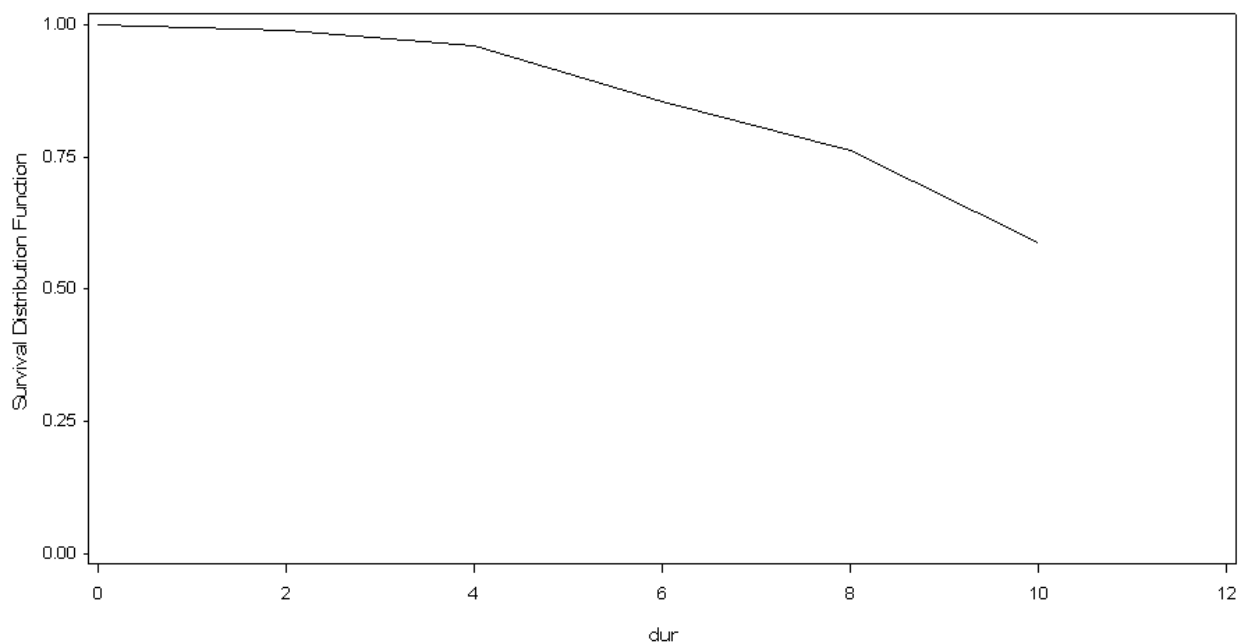


Figure 10. Plot of Survival Function over time

Next, Figure 11 gives a plot of the hazard function over time. Immediately, we can see that although it is jagged, it is certainly increasing over time. This is in line with one of the stylized facts of technology adoption: S-shaped pattern of diffusion. In addition, it makes intuitive sense that HIT adoption was slower at first and has picked up steam more recently.

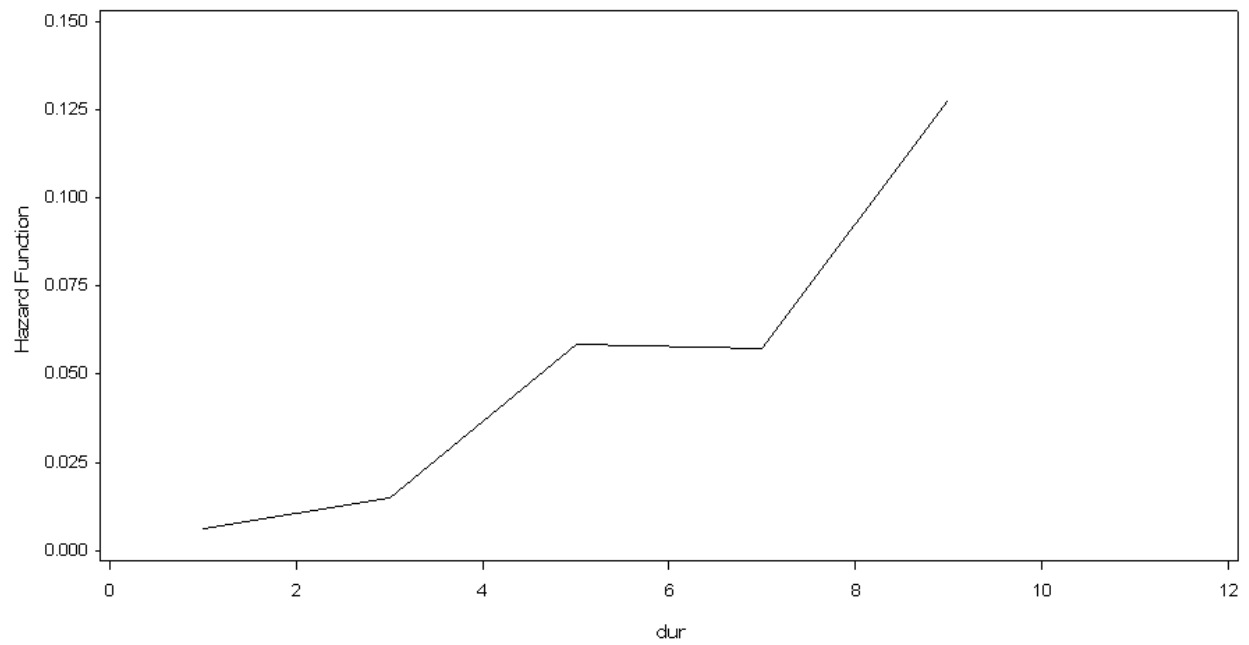


Figure 11. Plot of Hazard Rate over time

Next, the results from the exponential and Weibull AFT models are given in Table 6.

Table 6. Exponential and Weibull Model Results

	Exponential			Weibull		
Parameter	Estimate (Standard Error)	Chi- Square	Pr > ChiSq	Estimate (Standard Error)	Chi- Square	Pr > ChiSq
INTERCEPT	-16.5587 (19.2223)	0.74	0.389	-4.6558 (6.6062)	0.5	0.481
INCHAIN	-1.3551 (0.592)	5.24	0.022	-0.4669 (0.2052)	5.18	0.0229
YEAR OPENED	0.0105 (0.0096)	1.2	0.273	0.0039 (0.0033)	1.38	0.2405
PRACTICES PER 10000	-0.0077 (0.0168)	0.21	0.646	-0.0013 (0.0057)	0.05	0.822
INCHAIN*PRACTICES PER 10000	0.001 (0.0257)	0	0.97	-0.0017 (0.0088)	0.04	0.8495
COUNTY MEDIAN INCOME (1000s)	-0.0254 (0.0094)	7.24	0.007	-0.0106 (0.0033)	10.38	0.0013
INCHAIN*COUNTY MEDIAN	0.0168 (0.0118)	2.03	0.154	0.0062 (0.0041)	2.3	0.1298
NUMBER OF PHYSICIANS	-0.0337 (0.0393)	0.74	0.391	-0.0138 (0.0136)	1.03	0.3095
INCHAIN*NUMBER OF PHYSICIANS	0.0164 (0.0477)	0.12	0.732	0.0036 (0.0164)	0.05	0.8261
INTERNAL MEDICINE DUMMY	-0.1004 (0.2414)	0.17	0.678	-0.0585 (0.0832)	0.49	0.4822
MULTI-SPECIALTY DUMMY	-0.292 (0.1906)	2.35	0.126	-0.1618 (0.0664)	5.93	0.0149
PEDIATRIC DUMMY	-0.3592 (0.1702)	4.45	0.035	-0.1742 (0.0598)	8.49	0.0036
PRIMARY CARE DUMMY	-0.0226 (0.1706)	0.02	0.894	-0.0146 (0.0594)	0.06	0.8052
URGENT CARE DUMMY	0.7996 (0.2465)	10.53	0.001	0.3098 (0.0864)	12.86	0.0003
WOMEN'S CLINIC DUMMY	0.2336 (0.2695)	0.75	0.386	0.088 (0.0933)	0.89	0.3458
SCALE	1 (0)			0.3456 (0.0173)		
WEIBULL SHAPE	1 (0)			2.8936 (0.1449)		

In both AFT models, the first thing to notice is that the coefficients have the opposite signs as in the logit model. The reason is that AFT and logit are essentially modeling the opposite things. In the logit model, we are interested in the probability of adoption of EMR. In the AFT models, we are modeling the time to adoption. Thus, negative coefficients in the AFT models indicate a decreasing predicted time to adoption which is strongly correlated with an increased probability of adoption.

Most interestingly in this section, we notice that the SCALE parameter is estimated to be 0.345. This value indicates that the hazard rate is increasing over time and increasing at an increasing rate. This is very important from a policy perspective because it means that the rate at which clinic's are adopting is increasing over time, and it is consistent with the stylized fact of an S-shaped diffusion curve.

To get a better understanding of the predictions of these two models, we consider the eight example clinics from the logit model in Table 7. For clinics that are predicted to be early adopters of HIT, the predictions are very similar between the Exponential and Weibull models. However, there is a major difference in Predicted Year of Adoption for those that are predicted to be late adopters. This difference arises as a result of the Exponential model's assumption of constant hazard rate. Below, we discuss why this hypothesis is rejected. As noted above, the SCALE parameter of the Weibull model indicates that the hazard rate is increasing over time. For this reason, the Weibull models predictions should be more valid.

Table 7. Predicted Adoption Years of Eight Example Clinics for Exponential and Weibull Models.

Clinic Size	In Chain Status	Level of Market Competition	Predicted Year of Adoption (Exponential Model)	Predicted Year of Adoption (Weibull Model)
Small	Not in Chain	Low	2021	2010
Small	Not in Chain	High	2018	2010
Small	In Chain	Low	2010	2008
Small	In Chain	High	2008	2007
Large	Not in Chain	Low	2015	2008
Large	Not in Chain	High	2012	2008
Large	In Chain	Low	2008	2007
Large	In Chain	High	2006	2006

Finally, one good way to test the assumptions of the exponential and Weibull models is graphically. Figure 12 plots $-\log \hat{S}(t)$ which is the negative log of the survivor function. In order for the assumptions⁴ of the exponential model to be valid, this plot should be close to linear. From the Figure, we can see that this is obviously not the case, and this comes as no surprise since we saw earlier in Figure 11 that the hazard rate was increasing over time.

⁴ Namely that the hazard rate is constant over time

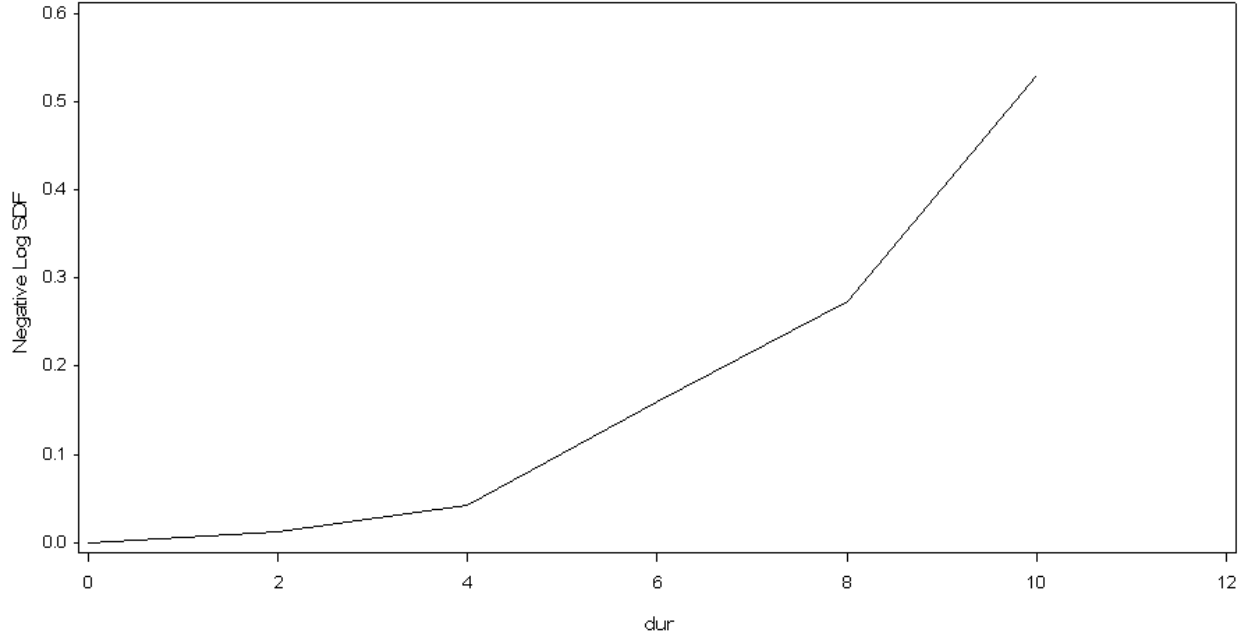


Figure 12. Negative Log of Survivor Function for Testing Constant Hazard Rate

Hypothesis

Similarly, in Figure 13, we consider the plot of $\log[-\log \hat{S}(t)]$. In order for the assumptions of the Weibull model to be valid⁵, this plot should be close to linear. In this case, the graph seems to indicate that the Weibull model's assumptions are valid in this case.

⁵ The Weibull model is equipped to handle an increasing or decreasing hazard rate, but not a hazard rate that is increasing, then decreasing, then increasing, etc.

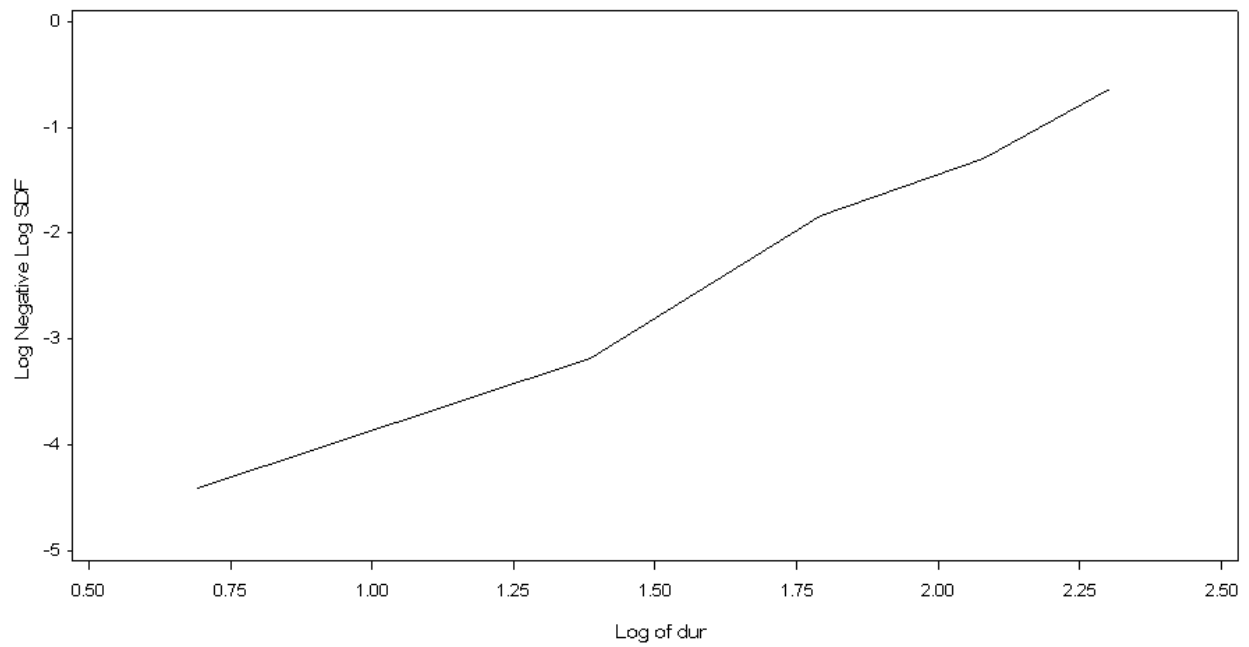


Figure 13. Log Negative Log of Survivor Function for Testing Assumptions of Weibull Model

Finally, the results of the Cox Regression are in Table 8.

Table 8. Cox Model Results

Parameter	Estimate (Standard Error)	Chi- Square	Pr > ChiSq
INCHAIN	1.46307 (0.58802)	6.1908	0.0128
YEAR OPENED	-0.01299 (0.00942)	1.9004	0.168
PRACTICES PER 10000	0.00537 (0.01672)	0.1033	0.7479
INCHAIN*PRACTICES PER 10000	-0.00142 (0.0253)	0.0031	0.9554
COUNTY MEDIAN INCOME (1000s)	0.02962 (0.00944)	9.8438	0.0017
INCHAIN*COUNTY MEDIAN INCOME(1000s)	-0.01737 (0.01171)	2.2011	0.1379
NUMBER OF PHYSICIANS	0.04222 (0.03923)	1.1587	0.2817
INCHAIN*NUMBER OF PHYSICIANS	-0.02276 (0.04756)	0.2291	0.6322
INTERNAL MEDICINE DUMMY	0.33272 (0.2245)	2.1964	0.1383
MULTI-SPECIALTY DUMMY	0.42371 (0.19119)	4.9111	0.0267
PEDIATRIC DUMMY	0.41693 (0.17096)	5.9476	0.0147
PRIMARY CARE DUMMY	0.04118 (0.17129)	0.0578	0.81
URGENT CARE DUMMY	-0.8429 (0.24189)	12.1424	0.0005
WOMEN'S CLINIC DUMMY	-0.14649 (0.25649)	0.3262	0.5679

Once again, the sign of the coefficients is reversed back from what we had in the AFT models. This is a result of the Cox regression modeling the hazard rate rather than the time to adoption. In this way, if the hazard rate is high, that means that firms are adopting faster implying that the time to adoption (what AFT models) is shorter. Once again, we find the same variables to be significant as in the first three models. This is not a surprising result at this point.

Since the Cox model does not estimate an intercept, we cannot make the same sensitivity analysis done for the previous three models.

6. Discussion

Overall, this paper presents a clearer understanding of the characteristics and competition effects that drive HIT adoption among small physician clinics. This paper gets around the criticism levied against most other HIT adoption papers of only studying the benefits to clinics which have adopted HIT by considering both non-adopting and adopting clinics and a data set with many more observations.

The factors that influenced EMR technology adoption did coincide with what the theoretical literature on general technology adoption proposed. The two major hypotheses that the paper sought to test were the effect of clinic size on EMR adoption and competition effects on EMR adoption. The results were strongly in favor of firm size being influential in determining a clinic's likelihood of adopting EMR – especially when being in a chain of clinics (which we have previously argued for being almost equivalent to bigger clinic size) is also taken into consideration. The results for competition effects did have the predicted direction, but the result was not statistically significant from zero in any model that was considered in the paper. Since the theoretical basis for competition effects was more tenuous than clinic size as well competition effects being more difficult to and less directly modeled than clinic size, this result is not completely surprising. More work in the future is needed to determine if there is indeed a competitive effect for EMR adoption and what exactly that effect is. A more disaggregated data set could be very useful for these purposes. Furthermore, several other factors were found to have a significant impact on HIT adoption that were not specifically accounted for in the technology adoption theory. First, firms located in counties with higher median incomes were more likely to be adopters of HIT. This could reflect either increased demand for health care

services leading to more investment HIT or increased demand for technologically savvy clinics by those with higher incomes. Second, the year that the practice opened was found to have an impact HIT adoption likelihood with older clinics being more likely adopters of HIT than newer clinics. In the context of the HIT literature, this could be a result of generally more financial stability for older clinics leading to an increased ability to purchase an expensive new technology with high sunk costs. However, with the amount of data that we have for this paper, this is only a suggestion for what might be causing this relationship. Finally, we found that Urgent Care clinics were much less likely to adopt HIT than the other types of clinics. Although this was not specifically a key test for the paper, it appears to be a reasonable result in the sense that Urgent Care clinics are less likely to see the same patients on a regular basis and therefore get less benefit out of investing in a way to keep better records for their patients.

There are several interesting extensions to this research that would be particularly useful. First, there are some interesting variables that could be added to a similar sort of paper. First, Hannan and McDowell (1984) included the wage rate for bank tellers in different locations as an explanatory variable in their model of ATM adoption. Similarly, including the wage rate for medical assistants by location would be an interesting variable to see if clinics are more likely to substitute technology for expensive capital. Also, more demographic factors could be added to the model. For instance, county level data on the health factors, education levels, and percentage of county residents having health insurance would all add interesting context to the model. Moreover, there is a need for quantitative research on the difference between urban practices and rural practices. Similarly, the effect of monopoly power on HIT adoption would be quite enlightening as well. Also, Survival Analysis models (in particular the Cox model) are equipped to handle explanatory variables that change with time. Although this paper did not utilize that

capability, many of the explanatory variables already presented in this paper and suggested in this paragraph do vary over time and could add to the power of the model.

In order to fully grasp what is going on in HIT adoption, much more extensive data needs to be collected on the cost of HIT systems. The market for HIT products is very confusing for those wishing to do research in this area. Wang and Miller give some estimates and breakdowns of “average” costs of EHR systems for ambulatory care practices. However, these numbers are very general and do not include variation and product characteristics which may account for relative price differences. Furthermore, to my knowledge, there is no source for pricing information for particular HIT systems. Moreover, visiting HIT vendors’ websites are not particularly useful either as the vast majority do not list a price for their product and appear to adjust it based on both the characteristics of the adopting practice and the practices negotiating skills. Similarly, for the theoretically minded, the technology adoption literature does not seem to be fully developed concerning a differentiated new technology where there is variety in the characteristics of the new technology and price of the new technology. With the large number of HIT systems currently available, any theoretical work leading to testable hypotheses coupled with a more complete data set of available HIT technologies and their prices would be a good avenue for future work.

Finally, the theoretical technology adoption papers concerning uncertainty in the value of a new technology or advances in the new technology seem to be particularly relevant for studying HIT adoption. In order to pursue this avenue of study, an empirical paper would require a very extensive, custom data set for individual clinics regarding their expectations of HIT technology and future prices. However, this type of research could prove to be quite useful in studying the question of HIT adoption in small physician clinics.

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