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Mesauring The Effect Of Technological Change In Health Care Cost And Expenditure

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MEASURING THE EFFECT OF TECHNOLOGICAL CHANGE IN HEALTH CARE COST AND EXPENDITURE

by

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DEDICATION

To the memory of

My beloved mother

Rukmini Devi Sharma

Whose love and support laid the foundation to grow this far

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CHAPTER 1

MEASURING THE EFFECT OF TECHNOLOGICAL CHANGE IN HEALTH CARE COST AND EXPENDITURE

1.1 Introduction

Technological change is the engine of increasing efficiency, fueling economic growth, and achieving a higher level of well being for the masses. It is argued that virtually all of the economic growth that has occurred since the eighteenth century is ultimately attributable to innovation (Baumol, 2002). Health care is one of the most critical areas with tremendous impact and improvement resulting from the innovation. There is a remarkable improvement in human health evident from increased life expectancy and health related quality of life, all owing to improved knowledge and uses of new technologies that impact human health.

A person born today has extraordinary possibilities and choices available in health care compared to one born fifty years or even twenty years ago. As a result, the consumption of health care has increased considerably in comparison with the past. It is reflected by the fact that health care consists of one of the largest shares of consumer expenditures in countries around the globe. Another part in the story of technological change is the price tag that is attached with the care. Along with spending, health care costs have increased tremendously in recent times. The increase in both cost and spending pose significant challenges to the performance and sustainability of a health care system.

Increased cost led to major concerns within the US health care system. Increased cost, for example, contributes to the pool of uninsurance, health care disparities, uncompensated care, and spillover effects to the general economy. In 1991, Peter J. Neumann and Milton C. Weinstein stated that at that time American society was approaching, or might have reached, the point at which it was not possible to provide the best available health care to every American, regardless of cost (Neumann and Weinstein, 1991). They felt the de facto solution of the problem was to restrict access to health care for a segment of the population like the uninsured while preserving the myth of best available care for those fortunate enough to have coverage. Almost two decades later, the statement proves to be blatant and correct. Technology is considered as one of the underlying causes of ever increasing health care cost.

Technological change can take place in different manners with different implications for spending and its growth. The most obvious change is to find a treatment that is not previously available. For example, if there is a new $10,000 effective treatment for Alzheimer's disease, which currently has no treatment, then there would be instantly thousands of new patients nationwide who want that treatment. This would almost certainly lead to large increases in health care spending. However, in most circumstances, technological change and its impact on spending is less obvious and subtle than this example.

We can think of technological change in terms of a change in the content of the composition of inputs used to provide care. This will create four possible scenarios:

Scenario I (*No technological change*): Same inputs are used over time. The cost of care depends upon how resource prices relatively change over time.

Scenario II (*Technological change*): Same inputs are used but in different intensity and/or combination so that there is an improved outcome.

Scenario III (*Technological Change*): New method of treatment is used comprising all or some of new inputs.

Scenario IV (*Technological Change*): Learning by doing—higher level of perfection and efficiency achieved by practicing methods over and over.

Whether a new technology actually increases cost or spending may depend upon other factors including whether the new technology adequately replaces existing treatment modalities and whether the new technology is more resource intensive. Further, the new technology may contribute to the rising costs of health care through each of the three distinct mechanisms: introduction, intensity of use and expansion (Gelijns and Rosenberg, 1994). Above all, rapid changes in health care technologies are facilitated by the technology friendly environment of the US health care system (Fuchs, 1996). There are plenty of incentives and minimal restrictions in the development, use and financing of new technologies in the US.

Technological change is widely accepted as a major driver of health care cost and expenditure in the US[1] and elsewhere. Increase in health care expenditure is attributed to several factors including ageing, insurance coverage, income, availability of care, etc. Technological advancement, however, is the single most important factor to explain the growth of expenditure believed to be ranging from over 50% to over 75% of the total increase (Newhouse, 1992, Gelijns and Rosenberg, 1994, and Fuchs, 1996). The main interest of this research is to quantify the association between technological change and increased spending over time.

1.2 General Objectives and Aims

The long term objective of this research is to seek an answer to the question: What is the share of technological change in the growth of health care cost and spending? This dissertation uses the case study of prostate cancer among the US elderly male population. In particular, this dissertation uses the information from cancer patients to measure the association between innovations in cancer care and associated change in spending in the period of 1990s and early 2000s. The research explores the question further to see how the health care spending of the people with cancer behaved over time given that there were some significant technological innovations and other subtle changes in care. The study hypothesize different

[1] In the US, the impact of technological change on health care spending and cost has become a national policy agenda. In 2003, a hearing was held before the Joint Economic Committee of the Congress on "Technology, Innovation, and Health Care Costs". Similarly, the Congressional Budget Office (CBO) published a report, "Technological Change and Growth of Health Care Spending", in 2008.

scenarios in order to tease out the association between technological change and treatment cost over time.

1.2.1 Specific Aims

In the next three chapters, specific scenarios are presented with specific assumptions and focuses. The main ideas behind these scenarios and their specific aims are briefly described here.

Part I: *(Technology specific to cancer care—an overview)* Imagine a scenario in which someone is diagnosed (DX) with condition X (cancer). How do pre- and post-diagnosis expenditure compare and behave over time? If post-DX expenditure grows faster, it will have important implications for technological change specific to X. As with DX comparison could be made about the treatment (RX), and specific treatments (SRX) and findings would give important implications about technological change in care associated with condition X.

From the scenario presented in part I, we can address two important research questions. The first research question is: How did the short term health care expenditure grow over time for the patients who were *diagnosed* of prostate cancer relative to those who were *undiagnosed* (of prostate cancer)?

Specific Aim 1: To calculate the historical trends of the short term health care expenditures to examine the differential growth of health care expenditures among patients who are *diagnosed* with prostate cancer

The second research question for this part is: How did the short term health care expenditure grow over time for the patients who were *diagnosed and treated* for prostate cancer relative to those who were *diagnosed but untreated*?

> **Specific Aim 2**: To calculate the historical trends of the short term health care expenditures to examine the differential growth of health care expenditures among patients who are *treated* for prostate cancer.

Part II: *(Productivity as an index of overall technology)* It is difficult to calculate an objective measure of technological change. As the productivity of care has consistently changed over time, so has the health care spending. Using appropriate analytical techniques and assumptions, I measure the association between the overall technological change and spending using productivity as a proxy for technology.

The research question associated with this part is: What is the association between overall change in health care technology and health care spending in cancer care? This amounts to finding the proportion of spending attributable to technological change in the area of general cancer care or treatment.

> **Specific Aim 3:** To construct and or use measures of overall technological change (technology index) in prostate cancer care and measure the association between technology index in prostate cancer care and short-term expenditures among people diagnosed with prostate cancer.

Part III: *(Technology as one of the inputs of care)* Suppose a new and better treatment A is introduced as a substitute for existing treatment B to treat a condition X. I estimate the incremental cost (IC) of A over B to see how IC behaves over time given that of A and B overlaps during that period. We can expect that trends for A and B have different intercepts, but what if they have different slopes? The slope is of specific interest and it has important implications.

The research question for this part is whether innovations in cancer treatment fuel the growth of cost and spending over time.

> **Specific aim 4:** To evaluate the growth of short term incremental health care expenditures associated with recent innovations in external beam radiation therapy—three dimensional conformal radiation therapy (3D-CRT) and intensity modulated radiation therapy (IMRT)—to treat prostate cancer.

The specific aims described here are associated with relevant hypotheses in respective chapters.

1.1.2 Concepts and Terms

In medicine, technological change includes a wide range of improvements including small changes such as increased frequency of a medication to major changes such as the plantation of an artificial organ. It is broadly defined to include any changes in clinical practice that enhance the ability of providers to diagnose, treat, or prevent health problems (CBO, 2008). Usually technological change

happens through gradual improvements and innovations on existing practices, techniques and treatments. The gradual and subtle nature of technological change poses empirical challenges to accurately define and measure the overall technological change and its aggregate effect on cost and spending.

Technological change in medicine may be narrowly defined just to include the introduction and diffusion of major changes in methods to provide care. Such methods usually require a significant amount of new knowledge, investment in new capital and additional training of the workforce. The use of minimally invasive surgery instead of open surgery, methods for an early diagnosis of cancer or prescription medication to prevent cardiovascular events may come into this category. Major advances in health care may contribute to most of the increase in cost and spending. This study also uses the definition of technological change in a narrower sense as well.

Here it is important to distinguish between the cost and spending. In order to define the cost, we must define the unit of output, which is tricky in health care. Health care has a multiplicity of attributes each with a certain value causing the same care worth more or less even if only one of the attributes changes. We need to factor out the quality in order to calculate the actual cost of health care. It is highly likely that the health care costs per quality adjusted unit may have actually become lower over time.

In order to avoid intricacies, this research does not use cost in its usual meaning in economics. Instead, it uses spending and cost equivalently as variables

of interest to measure the impact of technological change. Here in a broad sense, spending carries the concept of cost as well. For this purpose, health care is assumed to be a single commodity without factoring its characteristics that define its quality. If we assume that there is a single good or service named 'care' then health care spending is simply the cost of getting that care. This study assumes that there is one good or service called 'cancer care' and resultant spending is the cost of the care. The terms health care expenditure or health care spending are meant to be analogues.

It is also very important to determine how to measure the cost and spending which are the major variables of interest in the study. The question is what is the best measure of the cost or spending? There are two candidates—charges and reimbursements. The study uses charges rather than reimbursements as a measure of expenditure for a number of reasons. First, it is assumed that the cost of new technologies, which essentially enters the cost as an input cost, is more directly reflected in the provider claims without any lag. On the other hand, Medicare reimbursements rates might be less sensitive to the true cost of new treatment than charges. Second, the information about the payment might be incomplete in the dataset because payments are made from different sources. Third, the main purpose of this study is to see the incremental cost of new treatments using differenced rather than absolute expenditure values. So, differencing and using control group will take care of much of the bias resulting from the use of charges.

The charges used to calculate cost or spending are not limited to one particular condition or a cause. The charges used to calculate spending include the charges made for receiving care for any cause or condition for periods specified.

1.3 Significance of this study

Since 1970, the US health care spending grew by 2.4 percentage points faster than the growth in the GDP rising from 7.2% of the GDP in 1970 to 16.2% in 2007. In the US, health care spending as a percentage of GDP is also significantly higher than that of other advanced countries (Kaiser Family Foundation, 2007). The ever increasing health care spending presents an alarming picture of the future affordability and sustainability of the US health care system. It is estimated that a one-percentage-point gap between real per capita growth in health care expenditures and growth in GDP would be affordable[2] through 2075, while a two-percentage-point gap would only be affordable through 2039 (Chernew, Hirth and Cutler, 2003).

The financial projection made by Medicare in year 2000 is that for next 75 years the Medicare spending is going to grow by a percentage point higher than the growth of the GDP (Medicare, 2000). Unprecedented increase in health care spending puts a severe stress in public health care spending such as Medicare and Medicaid. The basic premise of such spending program is that government revenue is going to grow at the same rate wages and salaries grow. This eventually is going

[2] The affordability is measured in terms of the proportions of health spending in total spending. If health spending is equal of more than total spending it will be unaffordable.

to impose a restriction on the growth of public spending on healthcare. The check in expenditure growth over the real GDP is inevitable. However, the most critical question is when and how the check comes into effect.

It is widely agreed that technological advancement is a major factor fueling the growth of health care cost and spending (For example, Newhouse (1992), Gelijns and Rosenberg (1994), etc). One consequence of the technological change is that resources are reallocated from non-health to health goods. The health care technology is ever improving and if so does spending and its share in GDP, then there will be a point when we will need to decide: how much technological improvements can the society bear? Suppose there is a Medicare-like transfer program featuring a tax rate that adjusts to ensure that the people are allowed to consume health care as much as technologically feasible; then a critical parameter of the model turns out to be the maximum transfer rate that society is willing to tolerate (Jones, 2002). From this point of view, the question of interest is what is the socially optimum level of care and optimum level of technological advancement?

The outlook for future spending suggests that the effect of technology will remain as strong or get even stronger (Shactman et al. 2003; Strunk et al. 2006). The extent and nature of the relationship between technological advances in health care in the health care cost and spending is of a significant research interest with important implications for future health care policy making and reforms. In order to resolve the problems associated with growing health care cost and spending it is essential to understand the sources of such growth. As there is consensus about the

notion that technological change has the major role, there is relatively inadequate research and knowledge gap regarding the extent of such effect. Quantifying the effect of technology in percentage term would be an important contribution in this field.

The next important question about the effect of technological change in health care is the nature of the relationship between the technology and spending. This particularly leads to the question of how the technology is linked to higher cost and spending. New technologies do not always enter cost or expenditure function in a straightforward way. There are producers, consumers and markets for innovations in health care like any other industries. However, the health care sector is significantly different from other sectors of the economy due to the existence of asymmetric information, role of health care provider in decision making and third party payments for consumption. The mechanisms by which technology affects cost and spending can vary by the nature of technologies. For example, the rate of diffusion of cost saving improvements is much slower than cost increasing innovations in some instances (Stagier et al. 2009). There is not a single way technologies affect cost and spending. A better understanding of the ways technological change affects cost and spending will be helpful in health technology assessment, cost effectiveness analysis, projection of future spending and formulation of technology policy.

Understanding the role of technological progress in the growth of health care cost and spending is not only a matter of academic interest, but also an important

public policy interest now and in the future. Studies have found that countries with incentives to provide high tech procedures have experienced a relatively higher growth of those procedures suggesting that supply-side incentives determine high-tech changes (McClellan and Kessler, 1999). There will be a scope for a technology policy if increased spending is not commensurate with improved outcomes.

The significance of this study also is its focus on a major disease, cancer. Prostate cancer is the most prevalent cancer type among men. There has been substantial scientific focus on cancer care and treatment in recent times resulting in major advances in technologies and treatment innovations. Because cancer care is very expensive, it puts a significant pressure on health care financing including the public funding programs such as the Medicare. It is important to note that cancer primarily occurs in the senior populations aged 65 and older, the responsibility of Medicare.

Technological change in health care and their impact on spending has a lot to do to determine the future sustainability of Medicare. A projection of future spending in cancer care using the future elderly model finds that no scenario of technological change holds a promise guaranteeing the financial future of the Medicare (Bhattacharya et al., 2005). This study will shed a light on this issue through the proper understanding of the dynamic relationship of technology and cost in cancer care.

1.4 Data

This study uses the Surveillance, Epidemiology and End Results (SEER) Medicare-linked database which is created by linking two large population based sources of data. The data from Surveillance, Epidemiology and End Results (SEER) program of cancer registries is linked to data from Center for Medicare and Medicaid Services (CMS) of persons' Medicare claims for all covered services. The SEER part of data contains demographic, clinical and cause of death information for persons with cancer.

The Medicare part of data contains information associated with all eligible claims for corresponding cancer cases from SEER data. The Medicare part also contains information on date of service, diagnosis, procedures, provider type, claims and payments, and inpatient stays covered under the Part A and B of the Medicare program. Within the Medicare data, there are inpatient, outpatient and carrier claims. Medicare inpatient claims include all Part A short stay, long stay, and skilled nursing facility by calendar year. The outpatient data contains all Part B claims from institutional outpatient providers including hospital outpatient departments and other clinics and facilities. Carrier claims, also known as National Claim History (NCH) records, includes all Part B claims from physicians and other non-institutional providers.

The SEER database currently covers 26 percent of the US population by its 16 registry sites across the United States. However, this study uses the data covered by 13 SEER locations as of year 2002.

From the main database, subsamples were created based on the design of the study and focus. The selection of cases including the selection criteria, structure of analytical datasets are explained in the respective chapters.

1.5 Previous Literature

In the literature, there is a general consensus that technological change in health care is the main source of rising cost and expenditure. Although empirical research in this field is relatively limited, there are some studies to examine the relationship between the technological change and health care spending in one way or another. Fuchs (1972) found that between 1947 and 1967, changing technology contributed 0.6 percentage points to the annual 8 percent growth in health care expenditure. Another study (Altman and Blendon, 1979) found 10 to 40 percent increase in expenditure over time owing to technological change in health care. Most studies have focused on specific aspect of the issue such as specific health condition or treatment.

McClellan and Kessler (1999) did a global analysis of technological change in health care in the case of heart attacks. The study captures several aspects of technological changes in an international setting. One of the highlights from the findings of the study is that although many countries have lower levels of health care spending than the US but the growth rates of spending were very similar across the countries. It implies that the system factor determines the average level of health care spending in countries, while the technology determines its growth.

1.5.1 Technological change and its association with health care expenditure

The health economics literature points to different ways technological change may lead to increased health care spending. Geligns and Rosenberg (1994) discuss three distinct mechanisms by which technological change in health care may cause an increase in the health care spending. The first of such mechanisms is the *intensity of use* of existing technologies. The intensity of use of a particular technology for a particular condition can vary across countries and regions. In the US, intensive practice is seen in high-technology medicine due to the technology imperative environment shaped by a complex set of financial, professional, social and institutional factors.

Second, *introduction of new or modified technologies* provides a more subtle dynamics involved in technological change and associated health care expenditures. As new technologies are put in use, users provide their feedback to the developers. This feedback plays an important role in determining both the direction and rate of innovation efforts.

The third mechanism according to Geligns and Rosenberg refers to the *expanded applications* of available technologies. The indications for which technologies are applicable can always expand for more indications. For example diagnostic devices such as CT scanners and MRI devices have vastly expanded uses over time thereby vastly increasing spending.

It is important to note that medical technologies are not inherently cost increasing. Availability of new health care technologies usually brings a puzzling effect that they reduce the cost per treatment while increasing the overall expenditures at the same time (Huckman and Cutler, 2004). The solution to the puzzle is found if we look at another effect of technological change i.e. increase in utilization. Whenever there is an increased use of existing technologies or there are new technologies to make previously untreatable conditions treatable or new innovations that make existing treatment more effective and safer, the utilization of such technology increases significantly, causing a substantial increase in expenditures.

Another conundrum of the effect of technology is tied with presence of insurance. There are short-term and long-term effects of insurance tied with new technologies. The state of technology at a particular point of time determines the demand for insurance for that time. In short term, costly new technologies stimulate coverage, while improved coverage stimulates costs (Danzon and Pauly, 2001). The long term effect of insurance comes from its impact on R&D spending and nature and character of medical practice (Finkelstein, 2006).

Propensity to use a new technology is higher in the US as its healthcare system is friendlier to new technologies. The US health care system is built around a technologically friendly environment that inherently promotes newer technologies than elsewhere (Fuchs, 1986). The amount of resources going into the development of new technologies in part depends upon the future demand and financing for such

treatments. The long term impact of the interaction of R&D and insurance system is increase in health care expenditures (Weisbrod, 1991). The Wisbrod conjecture of impact of R&D, which is also a proxy for change in technology, on health expenditure is also supported by a study that uses the time series analysis of the long term relationship among aggregate real per capita health care expenditure, real GDP and total R&D spending in health sector. Data between 1960 and 1997 support the strong and stable impact of technological progress in raising health care expenditures (Okunade and Murthy, 2002).

The tendency to use new technologies is such that even the health management organization (HMO) system, which is effective in curtailing the cost of care in different ways, is ineffective to constrain the use of emerging medical technologies. A study in the case of gallbladder surgery shows no systematic difference between HMO and general population in the rate of growth of utilization of the new technology (Chernew, Fendrick, and Hirth, 1997). Evidence from the diffusion of MRI suggests that HMOs may be able to reduce health care costs related to latest technologies only by influencing the adoption of new medical equipment and technologies (Baker and Wheeler, 1998).

In recent decades, increased R&D spending is devoted to the development of drugs that eventually lead to the increase of prescription drug spending. The introduction of successful new products through expensive R&D combined with an ageing population, third party prescription drug coverage, and better diagnostic techniques has swelled drug spending in the United States (Pammolli, and

Roccaboni, 2004; Berndt, 2004). Constant feeding of new technologies into the system can render any other approach of reducing cost ineffective. Aaron and Schwartz (1990) review the past efforts at reducing health outlays in the US and found that measures such as increased regulation and competition among providers has resulted in an one time saving. They conclude that if new technologies are introduced in an unchanged rate, the main underlying force that has driven up cost and spending would remain intact (Aaron and Schwartz, 1990).

1.5.2 Technology and disease specific impact on health care expenditure

There is increasing evidence that the availability of new and advanced technologies often causes an increased rate of utilization of procedures causing a significant rise in average spending. Technologies such as coronary artery bypass graft (CABG) required more capital and labor including the more expenses associated with spread of knowledge, compared to alternative treatment some 35 years ago. Availability of technologies including CABG, imaging technologies, neonatal intensive care units, and radiation oncology facilities is associated with a greater per capita use and higher spending on these services (Bodenheimer, 2005). A disease level study by Cutler and McClellan (Cutler and McClellan, 2001) calculates the cost of technological change in four different conditions. The study finds substantial increase in cost due to technological advancement. For example, in heart attack patients, technological change accounted for more than 50% increase in the cost of treatment during the period from 1984 to 1998.

Several empirical studies relate availability of new technologies to increased utilization and higher health care expenditure. There are other studies that look into selected technologies. Baker et al. (2003) analyzed the relationship between the supply of new technologies and health care utilization and spending, focusing on some key technologies. The study found a positive relationship between the availability of those technologies and amount of spending. A study (Cindy et al., 1998) of the supply and use of five key medical services found that the growth in supply of medical technologies has exceeded the growth in utilization, which in turn has created excess capacity that can increase cost.

A study of the relationship between magnetic resonance imaging supply and low back pain for Medicare patients by Baras and Baker (2009) found that increases in MRI supply are related to higher use of both low back MRI and surgery even though the usefulness of the procedures are not established. A study on countries under Organization for Economic Co-operation and Development (OECD) compared the number of specific health care facilities and per capita health care expenditures. It found that there is a positive relationship between the number of cardiac surgery facilities, cardiac catheterization laboratories, revascularisations, CT scanners, MRI machines and average health care expenditures across countries (OECD, 2003).

1.6 Recent technological changes in prostate cancer care

The current available treatment options for prostate cancer are based on the stage of cancer. Watchful waiting is treatment option for older patients especially

with low grade cancer presentation. Among the available treatment options, the most common are radical prostatectomy, external beam radiation therapy, implant radiation therapy and hormone therapy. Radical prostatectomy and radiation therapy are also known as definitive treatments while hormone therapy is mostly used as adjuvant or neo-adjuvant treatment. There are new type of treatments being tested in clinical trials including cryosurgery, chemotherapy, biologic therapy, high intensity focused ultrasound and proton beam radiation therapy(NCI, 2009 web access).

The most advanced form of therapies used today in prostate cancer treatment and care were developed in the 1980s and 1990s. The most notable events include the finding of prostate-specific antigen (PSA) as an indicator of prostate cancer (1980), use of Luteirizing (1981), nerve-sparing prostatectomy (1983), ultrasound guided implantation of radio-active seeds (1983), FDA approval of Leuprolide (1985) and PSA test (1986), ultrasound guided biopsy device (1988), FDA approval of Flutamide (1989), development of three dimensional conformal radiation therapy (1990), and FDA approval of PSA screening for the detection of early prostate cancer (1994) (Denmeade and Isaacs, 2002*).* Use of PSA screening as an early detection tool for prostate cancer led to a significant change in the care of prostate cancer. Cancers were detected at early stages and treated with higher intensity treatments like radical prostatectomy. This led to a decline in prostate cancer mortality first time in history and overall reduction of prostate cancer death rate related to prostate cancer screening is as much as 62 percent (Agalliu et al., 2007*).*

During the period for this study, no significantly new treatment was introduced other than innovations in the existing therapies. A recent innovation in surgical option for the prostate cancer treatment was minimally invasive radical prostatectomy (MIRP). Also known as laparoscopic radical prostatectomy, minimally invasive surgery involves the use of equipment with a small incision as opposed to large incisions in open form of radical prostatectomy. This technique gave rise to a new era of robotic prostatectomy as a major form of MIRP. From 2003 to 2007, the number of MIRP procedures increased from one percent to more than 40 percent of all prostatectomies (Hu et al, 2009).

There have been significant changes in radiation therapies—both external and internal. In external beam radiation therapy (EBRT), the first and most notable change was the development of three dimensional conformal radiation therapy followed by intensity modulated radiation therapy. Three dimensional therapy replaced existing two dimensional dose planning system. The conformal therapy is based on an advanced imaging system that enables the precise targeting of cancer cells with larger radiation doses. The result is improved clinical effectiveness with less complication. The intensity modulated therapy which came into effect during late 90s is more advanced than three dimensional technique.

In internal radiation therapy, which is known as brachytherapy, radioactive seeds are implanted in the cancerous tissues. These seeds produce radiation locally destroying the surrounding cells. The most recent and notable treatment innovations using brachytherapy are ultrasound guided transperineal permanent

brachytherapy of the prostate, and high dose rate brachytherapy. Internal beam radiation therapy is gaining increased popularity more recently with a projection that about one third of all localized prostate cancer patients will be choosing this option by the year 2005 (Thomadsen, 1999).

Hormonal therapy, also known as the androgen deprivation therapy, is another widely used treatment option for prostate cancer patients. Unlike the surgery and radiation therapy, androgen deprivation therapy is used along with other therapies in adjuvant[3] and neo-adjuvant settings. There was a substantial increase in the use of androgen ablation therapy both as primary treatment and adjuvant treatment between 1989 and 2001. A study finds that as a primary treatment, the treatment rate using androgen deprivation therapy was 48 percent among high risk groups in 2001. In the same year 75 percent of patients receiving radiation therapy were given androgen ablation as an adjuvant treatment (Cooperberg et al., 2003). The diffusion and utilization rate of androgen ablation treatment is growing faster than any other treatments for the condition.

1.7 Basic Model

Health care spending depends on several factors including the consumer preferences between health and non-health goods, prevalence of diseases, availability of care, health care policy, and system characteristics. At the individual level, the health care spending depends on the different set of factors within the

[3] Adjuvant therapy is given after the primary therapy and neo-adjuvant therapy is given before primary therapy.

given health care setting. The relationship between the individual spending and factors determining care can be summarized in the following functional form:

$$EX = f(X, Y, V, M, T, C) \qquad (1)$$

where, EX denotes health care expenditure at individual level, X denotes individual characteristics including age, sex and insurance status, Y is provider characteristics, V is system characteristics, M is market features, T is level of technological advancement, and C is health care conditions including the incidence of diseases in the population.

Consider simple estimation equation in the following form:

$$EX_{ijt} = \beta \boldsymbol{X_{ijt}} + u_{ijt} \qquad (2)$$

where, EX_{ijt} is spending by individual i with condition or treatment j at time t and u_{ijt} is the unexplained residual. Following Newhouse (1992), $\boldsymbol{X_{ijt}}$ includes all the observed factors determining the demand for medical services that are included in equation (1) above other than technological change. Here technology is considered as residual—the part that is unexplained by all other factors is effect due to the variation of technology in health care.

This approach to account for technological change is not without problems. Newhouse (1992) accepts that trying to attribute a residual to specific factor is an inherently frustrating exercise. However, he also believes that this is the best that can be done. Since the residual error term includes all the impact resulting from technological change, the next question is how to account for the growth rate of the residual.

The first thing in the accounting is to use a cross section estimate of β to estimate the residuals as $EX_{ijt} - \widehat{EX}_{ijt} = \hat{u}_{ijt}$. After the calculation of the residual, the next task is to determine what explains the residual change including how much of the residual is attributable to the new capabilities of medicine. Suppose we are able to observe the residual $\hat{u}_{ijt}$ for a number of years. Our interest then is to find its growth rate as:

$$\hat{u}_{ijt} = \hat{u}_{ij(t=0)} \exp(\theta t) \qquad t = 0, 1, 2, \dots, T \qquad (3)$$

where, θ denotes the growth rate of the residual, a measure of change in health care expenditure caused by technological changes. Taking logarithms on both sides

$$\begin{aligned} log(\hat{u}_{ijt}) &= \log(\hat{u}_{ij(t=0)}) + \theta t \\ \Omega_t &= \alpha_0 + \theta t \\ \Omega_t &= \alpha_0 + \theta t + \varepsilon_{ijt} \end{aligned} \qquad (4)$$

where, in the last equation ε_{ijt} is a random error term, α_0 is log of starting value of the residual and θt is cumulative technology component. The last is an estimable equation by a regression technique.

Equation (4) decomposes the residual term into three different components. The inherent assumption used in (4) is that technology changes in a continuous and smooth fashion. This assumption, however, is not realistic in health care spending. It is true that there are countless infinitesimal changes in medical practice every year contributing to both health care technology and spending. There are also some significant changes that may give a 'shock effect' to the health outcome and cost. In

this 'shock' scenario, the technology component is decomposed into two different parts—steady and sporadic. For this scenario, equation (4) can be rewritten as

$$\Omega_t = \alpha_0 + \alpha_t + f(\text{shock}_j) \qquad (5)$$

here α_t is a secular component that explains efficiency improvement that is common across the industry, such as the use of a certain diagnostic technique. The second term $f(Shock_j)$ is the shock function that captures the effects of the introduction of a new technology that is specific to a certain condition. Equation (5) is a basic form of the model. There can be different ways to specify an estimation equation for model (5). Here is one of the full specifications of the equation (5) above.

$$\Omega_t = \alpha_0 + \alpha_t + \beta_{jt} + \sum_{j=1}^{n}\left[\lambda_{jt}(\text{shock}_j * \mathbf{1}(Year_t \geq T) + \delta_{jt}\left(\text{shock}_j * \mathbf{1}(Year_t - T)^2\right)\right] + \varepsilon_{ijt} \qquad (6)$$

Here $\beta_{jt}$is the treatment specific fixed effect and λ_{jt} and δ_{jt} capture the fixed effects and quadratic effects of the shocks respectively. We can introduce a time lapse term in the equation (6) above to capture the effect of the expansion of the shock or so called "intensity of use" of a certain treatment.

The model discussed above is very basic and it may not fit different situations that potentially exist. Most importantly, it is very challenging to empirically implement. First, the calculation of the residual that purely includes technology factor and random error is very difficult. It is because the residual may include many unobserved factors affecting expenditure, not only technology. It is empirically not feasible to include every possible factor that affects health care

spending in the estimation equation. Second, even if we can control for all factors affecting spending, they may not be independent of the technology factor. The independence of technological change is necessary in order to have an unbiased estimate of β in equation (2).

Even if the residual is decomposed from total expenditure, it is too strong to assume that technology is the only factor causing its growth. There can be other factors that are correlated with health care technology that might also affect spending. For example, like technology, there is an increase in obesity over time that also significantly affects health care spending. If the effect of increase in obesity is also included in the residual term, then the effect of technology will be highly overstated from the model above.

It is methodologically challenging to estimate the effect of technological change in health care expenditure. In this study, I have used different but empirically sound and proven methods to make some inferences about the effect of technological innovations in health care. Following this chapter, each chapter has the outline of the theoretical construct and empirical approach to calculate such an effect of technological changes.

1.8 Chapter Summary and Conclusions

Like all other parts of a modern economy, health care has changed tremendously over time due to technological advancement. However, the achievement has come with a huge price tag. The resulting growth of health care spending and cost has become a serious matter of concern.

Previous literature in this area is relatively scarce. There are studies that go back as early as 1970s and 1980s that people began to worry about growing health care spending. This area of study received more focus during 1990s and onwards. Many studies link technology with growing health care cost in the US. It is widely agreed that technological advancement has a dominant role in ever increasing health care expenditures. Any effort now or in the future to manage or curtail health care cost has to deal with technological changes. There is an increasing scope for technology policy in that regard in order to make sure that the choices made in health technologies are efficient. It is also important to know the extent and nature of the relationship between technological change and health care spending. This research seeks to understand how new technologies affect health care expenditure and how much.

In order to meet the objectives of research, this study creates different scenarios to make inferences about the extent of the impact of technological changes. I use the case study of US elderly male population who are diagnosed with prostate cancer and who are available in SEER Medicare-linked database from 1991 to 2002.

In the next three chapters, I use various study designs and techniques to quantify the relationship between health care spending and technological changes in the study population. These three chapters are independently designed and have no relationship with one another. The last chapter is devoted to summary and conclusion of the whole study.

CHAPTER 2

HEALTH CARE EXPENDITURES: THE PICTURE IN LONG RUN

2.1 Introduction

Let us define growth picture as an overview of how health care costs related to prostate cancer (PCa) care have changed during the study period (1991-2002). The long run behavior of health care expenditure portrayed in a growth picture helps to understand the nature and direction of the growth. The growth picture also provides an overall view of how health care expenditure has changed in the long run. The main goal of this chapter is to obtain a growth picture of expenditures associated with prostate cancer care and derive implications for technological change in prostate cancer care.

The growth in spending is not influenced by all factors in equal proportions. For example, the cost of an office visit of a physician may be relatively stable over time while the cost of an emergency room visit may have significantly changed. One of the strategies in deriving implications for technological change is to classify expenditures in different groups and categories, and do a comparative analysis of the growth in each expenditure group.

Cancer care is given considerable attention in the United States. There has been considerable investment in finding a better cure or improving the quality of existing care. Every year, billions of dollars are spent in cancer related research from both public and private funding sources. The annual budget of National

Cancer Institute, a government funded program, alone reached above 5 billion dollars in the year 2010 (Kaiser, 2010). As a result of this there have been tremendous changes in cancer care in recent history including PCa care.

The research questions addressed in this chapter are whether health spending associated with cancer care grew faster than average health care spending and how much of the additional contribution to health care cost came from technological advances in cancer care. This chapter focuses on finding a relative growth of cancer care spending resulting from changes in cancer care technologies compared with all other conditions. The finding from this analysis will give some idea whether there is a significantly different growth in spending for cancer care compared to the other medical conditions. The analysis is limited to cost or expenditure related to prostate cancer care.

In accordance with the specific aim I and II of this research presented in Chapter 1, the study hypotheses for this chapter are stated here.

Hypothesis I:

H0.1: The growth trend in total health care expenditure in men *diagnosed* with PCa is the *same* as those without PCa in the study period.

H1.1: The growth trend in total health care expenditure in men *diagnosed* with PCa is *different* from those without PCa in the study period.

Hypothesis II:

H0.2: The growth trend in total health care expenditure in men diagnosed with and *treated* for PCa is the *same* as those without PCa in the study period.

H1.2: The growth trend in total health care expenditure in men diagnosed with and *treated* for PCa is *different* from those without PCa in the study period.

Hypothesis III:

H0.3: The growth trend in total health care expenditure in men *treated* for PCa with different methods is the *same* as those without PCa in the study period.

H1.3: The growth trend in total health care expenditure in men *treated* for PCa with different methods is *different* from those without PCa in the study period.

Each of the test variables in this analysis is a measure of historical health care expenditure on PCa at the individual level. Comparison of expenditures is made in terms of their trends. To this purpose, the first step is to calculate the cost associated with PCa care—its management and treatment.

A quasi experimental design technique is used to calculate health care cost for cancer management or care. An analytical dataset was prepared by restructuring the data in a quasi experimental form. The SEER database contains

the population of all cancer patients living in various geographic locations of the US. The diagnosis of cancer is assumed to be a random event—unrelated to previous or potential spending of a patient. The cost of cancer management is simply the difference between pre-diagnosis and post diagnosis health care expenditure.

The standard approach of calculating incidence cost of cancer is the incremental cost of cancer patients compared to matched non-cancer patients (Barlow, 2009). This is also known as the net cost of disease incidence. The technique of calculating net cost of cancer as the difference between cancer patient and similar non-cancer patient cannot account for the patient level or area level fixed effect. In this study, I have used a more rigorous approach that compares a random sample of cancer patients with non-cancer patients in terms of their both pre-diagnosis cost of care and post-diagnosis cost of care.

2.2 Theoretical Construct

In this section, I discuss some theoretical background to the empirical analysis of health care expenditure. What is the theoretical framework for the determination of health care spending? Studies that analyze health care expenditure usually lack an economic model that can justify the use of an empirical model. In the economic literature, there has not been much work on theoretical background of the health expenditure function. Here I am briefly describing the theoretical aspect of the expenditure function.

With different attributes, health care is one of the goods and services in the consumption basket of individuals. Health care has buyers and sellers in a market like setting, and price of health care is determined by the interaction between the buyers and sellers. For analytical simplicity, let us treat health care as a single good that can vastly vary in its features and attributes. The price of health care is then the total amount of spending made on health care during a particular period of time, say a year. Let us define a year of care as one unit of health care and the total spending made on one unit of care as the unit price of health care. The price of health care is not the same for every individual—it varies depending on the type and attributes of care one has received. Each person is essentially getting a different care—the same good but with different attributes. For example, sicker people receive vastly different health care than healthier people. Even one healthy person gets a slightly different care than other healthy persons.

So health care is a single good with multiple attributes. The unit price of health care or total health care spending in a year therefore depends on the attributes of the care one receives. In economics, situations like this are modeled using the hedonic price model[4]. Let health care be z defined by a good with n measurable characteristics such that $\boldsymbol{z} = (z_1, z_2, \ldots z_n)$ and price $P(\boldsymbol{z}) = P(z_1, z_2, \ldots z_n)$ is defined for each point in the vector space $\boldsymbol{z}$. $P(\boldsymbol{z})$ is also known as a hedonic function.

Let us define a utility function for consumers as (Ekeland et al., 2002)

[4] Here I am following Ekeland, Heckman and Nesheim, 2002 and 2004, and Nesheim, 2006

$$U(c, \boldsymbol{z}, \theta, A) = R + P(\boldsymbol{z}) + \theta' z + \frac{1}{2}\boldsymbol{z'Az} \qquad (2\text{-}1)$$

where, A represents preference parameters common across persons, θ represents preference heterogeneity parameters that differ across people and $c = P(\boldsymbol{z}) + R$ is consumption (where, R is unearned income).

The economic profits of suppliers that sell health care are defined as

$$\prod(\boldsymbol{z}, \boldsymbol{v}, B, P(\boldsymbol{z})) = \boldsymbol{v}'\boldsymbol{z} + \frac{1}{2}\boldsymbol{z}'B\boldsymbol{z} + P(\boldsymbol{z}) \qquad (2\text{-}2)$$

where, B represents common technology parameters, $\boldsymbol{v}$ represents a vector of technology parameters that differ across firms. It is assumed that $\dim v = \dim \theta$[5] and neither of the two are observable to the researcher.

The first order conditions are:

$$\theta - Az - P_z = 0 \text{ , and}$$

$$v - Bz - P_z = 0 \qquad (2\text{-}3)$$

The equilibrium is obtained by equalizing the demand and supply densities at each values of $\boldsymbol{z}$ and solving the linear differential equation. In normal linear and quadratic case the solution is quadratic in $\boldsymbol{z}$ (Ekeland, Heckman and Nesheim, 2002 and 2004). The solution is written as:

$$P(\boldsymbol{z}) = \pi_0 + \pi'_1\boldsymbol{z} + \frac{1}{2}\boldsymbol{z}'\pi_2\boldsymbol{z} \qquad (2\text{-}4)$$

where, $\pi_1$and π_2 are parameters of interest. To determine $\pi_1$and $\pi_2$we need to utilize the equilibrium condition in the market. In market equilibrium, each firm chooses (z_i, p_i) to maximize profits. The equilibrium hedonic prices $P(\boldsymbol{z})$ and

[5] Here dim means dimension of the vectors

characteristics $\boldsymbol{z}$ are determined by the distribution of buyers and their preferences, the cost and technology of firms and structure of the market (Nesheim, 2006).

The ultimate goal of hedonic price models is to estimate both preference and technology parameters. This has become a tricky and controversial issue in the economics literature[6]. However, the main purpose of this discussion is to explore the theoretical underpinnings of a pricing function, and it is not intended to estimate the preference and technology parameters. By exploiting information from the equilibrium conditions, including product attributes, demand, supply and price we can estimate the pricing function above. We can write a marginal price function in terms of $\pi_1$and $\pi_2$as

$$P(\boldsymbol{z}) = \pi_1 \boldsymbol{z} + \pi_2 \boldsymbol{z} \qquad (2\text{-}5)$$

Under certain assumptions this pricing function can be directly estimated by using regression techniques. Economic theory of hedonic price models does not put any restriction on the functional form of such equations. The functional forms of the price models are, therefore, arbitrarily chosen.

2.3 Empirical Strategy

The empirical analysis for this chapter is designed to identify the incremental effects of diagnosis of prostate cancer, treatment of prostate cancer, and the treatment of prostate cancer with specific treatments. A general form of estimation equation is given as

[6] See Eakland, Heckman and Nesheim, 2004 for detail

$$p_t = \mathrm{g}(\mu_0 + \boldsymbol{z_t}\beta + \gamma . D_t + \varepsilon_t), \qquad (2\text{-}6)$$

where D_t is a vector of time dummies. This model is also known as a price index model used to adjust for hedonic quality adjustment[7]. This version of the hedonic model will be the most suitable for the analysis in this chapter.

There are different estimation methods available. Health care cost data demand special treatment from the analysts due to their idiosyncratic distribution. There are several studies on the cost that use different estimation strategies: (1) Ordinary Least Squares (OLS) regression in raw scale, (2) log-OLS regression, (3) Generalized linear models (GLMs) . The OLS based models with logged dependent variable are less precise than generalized linear models (GLM) for certain data generating processes (Manning and Mullahy, 2001). However, more recent literatures (Basu et al., 2005) suggest other estimators that appear to be more precise and suitable for the data generating processes in the health care costs. Below I briefly discuss the methods that I plan to use to estimate the regression models.

2.3.1 Generalized Linear Model (GLM)

Following Manning et al. (2005) the estimation of the regression models using maximum likelihood for a specific distribution—the generalized Gamma—performs well against the alternative estimators. A simple health care cost regression model involves a response variable y as a function of vector $\boldsymbol{x} =$

[7] For a detailed discussion of hedonic price adjustment model see Triplett (2004).

$(x_1, x_2 \ldots, x_p)$ of covariates for the mean function. The interest generally lies in one or more of x_j in the response function. If the response function is exponential, the conditional mean of the marginal effect can be denoted as:

$$D_j(\mu_j, x) = \frac{\partial \mu(x)}{\partial x_j} = \beta_j e^{x_j \beta} \qquad (2\text{-}8)$$

Let $Y_i,\ i = 1, \ldots, n$ be independent measurements. Generalized linear models for independent data are characterized by a systematic component as featured in (1) and a random component following a probability distribution from an exponential family: binomial, Poisson, normal, Gamma and inverse Gaussian.

For the generalized Gamma distribution, the expected value of y conditional on x is given by:

$$E(y|x) = exp\left[x'\beta + \left(\frac{\sigma}{x}\right)\ln(\kappa^2) + ln\left(\Gamma\left\{\left(\frac{1}{\kappa^2}\right) + \left(\frac{\sigma}{\kappa}\right)\right\}\right) - \ln\left(\Gamma\left\{\left(\frac{1}{\kappa^2}\right) + \right\}\right)\right] \qquad (2\text{-}9)$$

An estimator for the marginal effect of a covariate x_j on the expected value of y is then given by:

$$\frac{\partial \ln\left(E(y|x)\right)}{\partial x_j} = \hat{\beta}_j + \frac{\hat{\kappa}}{\ln\left(\hat{\kappa}^2\right)}\frac{\partial \hat{\sigma}}{\partial x_j} + \frac{\Gamma'(\theta)}{\Gamma(\theta)}\frac{\partial \hat{\sigma}}{\partial x_j}$$

$$j = 1, \ldots, p$$

where, $\theta = \left[\left(\frac{1}{\kappa^2}\right) + \left(\frac{\hat{\sigma}}{\hat{\kappa}}\right)\right]$, $\frac{\partial \hat{\sigma}}{\partial x_j} = \hat{\sigma}\left[\hat{\alpha}_1 f'(x)/f(x)\right]$, and $\frac{\Gamma'(\theta)}{\Gamma(\theta)}$ is a digamma function. When σ is not modeled as a function of x, then the estimator for $\frac{\partial \ln\left(E(y|x)\right)}{\partial x_j} = \hat{\beta}_j$ (Manning et al., 2005).

The maximum likelihood estimator of the parameter vector is obtained by solving the estimating equations

$$D'V^{-1}(Y-\mu)=0 \qquad (2\text{-}10)$$

where, $\mu = g^{-1}(X\beta)$, and

$$D=\frac{\partial\mu}{\partial\beta}\begin{bmatrix}\frac{\partial\mu_1}{\partial\beta_1} & \cdots & \frac{\partial\mu_1}{\partial\beta_p}\\ \vdots & \ddots & \vdots\\ \frac{\partial\mu_N}{\partial\beta_1} & \cdots & \frac{\partial\mu_N}{\partial\beta_p}\end{bmatrix}$$

The solution to the GLM estimating equations is asymptotically multivariate normal with mean equal to and covariance matrix

$$\sigma^2[D'V^{-1}D]^{-1}$$

2.3.2 Generalized Estimating Equations (GEE)

Let Y_{ij} represent the j^{th} measurement on the i^{th} subject. There are n_i measurements on subject i and $\sum_{i=1}^{k} n_i$ total measurements. Correlated data are modeled as Generalized Estimating Equations (GEE) for estimating β. GEE is an extension of independence estimating equations (GLM) (5) using the same link function, linear predictor setup, variance function, and an additional covariance structure of the correlated components. The estimating equations can be written in the form

$$\sum_{i=1}^{k} D'V^{-1}(Y-\mu)=0 \qquad (2\text{-}11)$$

where $D_i=\frac{\partial\mu_i}{\partial\beta}$. The solution to the GEE gives a consistent estimate of β that is asymptotically multivariate normal with covariance matrix

$$\sigma^2[D'V^{-1}D]^{-1}=\sigma\left\{\sum_{i=1}^{k}[D_i'V_i^{-1}D_i\right\}^{-1}$$

In the data, correlated measures are pre- and post-period individual expenditures and GEE is a suitable technique for the data.

2.4 Empirical analysis

2.4.1 Sample design

Analytical samples of data were constructed for the purpose of this analysis. The overall study population included a fraction of the US population who were diagnosed with prostate cancer between 1991 and 2002. I have used the pre-cancer information of a group of patients serving as the comparison group for the analysis. So, the patients in comparison group were treated as if they never had cancer. For analytical purposes, the study population was put into four different categories.

Category I (*Population without cancer*): This category was created from the study population from a random selection of individuals before they were diagnosed with cancer. The dataset contains the history of claims of all individuals from 1991 to 2005 if they were enrolled in Medicare Part A and B during that period. Even though they were eventually diagnosed with prostate cancer, their selection was for their pre-diagnosis cancer free period. These cases were not included in any of the categories of cancer diagnosed patients described below.

Category II (*Population with cancer diagnosis*): These cases, who serve as one of the treatment groups, were selected from the overall study population for their post diagnosis information. This includes all the people who are not in category I and

who have claim history of at least 320 days following the diagnosis of cancer. This category includes all PCa patients irrespective of their treatment status.

Category III (*Population diagnosed with and treated for cancer*): This group includes a subset of category II individuals who are treated for prostate cancer with either radiation therapy or by radical prostatectomy within 4 months of the date of diagnosis. The use of 4 months period is due to two reasons. First, 4 months is a standard period within which most patients get a treatment intervention. Second, adequate follow-up time (in this case it is 8 months to one year) is required in order to capture all treatment related expenses. Category II cases serve as another treatment group for the analysis.

Category IV (*Population diagnosed with cancer and treated with radiation, surgery or neither method*): This category includes Category III cases which are divided into three groups. Group 1 and 2 include those who received the treatment by surgery and by radiation respectively within 4 months of diagnosis. Patients receiving both treatments were put in Group 1 because radiation therapy could be given as adjuvant or neo-adjuvant therapy. There is a third group which includes individuals who receive neither of the two treatments within 320 days following the date of diagnosis. The rationale for distinguishing patients by the type of treatment received is to differentiate them by their clinical characteristics. It is important to note that surgery and radiation are two definitive treatments for prostate cancer. Surgery is generally administered to healthier and younger patients with better

prognosis and initial stage of tumor growth. Patients receiving radiation therapy are more likely to be sicker, older and in more invasive stage of their cancer growth.

For each category an anchor date is created in order to define a pre-diagnosis period and post-diagnosis period and calculate total spending for each period for each category of individuals. The anchor date was the date 45 days prior to date of diagnosis for treatment group and 410 days prior to the date of diagnosis for comparison group. The use of 45 days before the date of diagnosis intended to capture all diagnosis related expenses regarded as a part of the total cancer care expenses. The pre diagnosis period is 365 days preceding the anchor date and post period consists of 365 days following the anchor date. Figure 2.1 (*a* and *b*) shows a sketch of sample selection timeline.

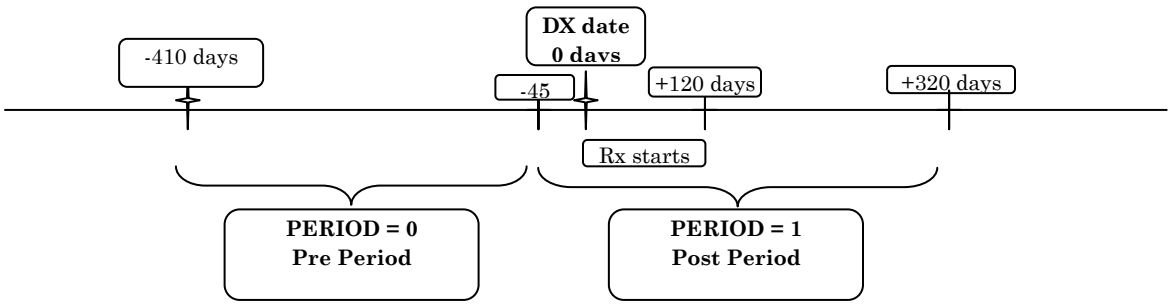


Figure 2.1 (a) Timeline for treatment group

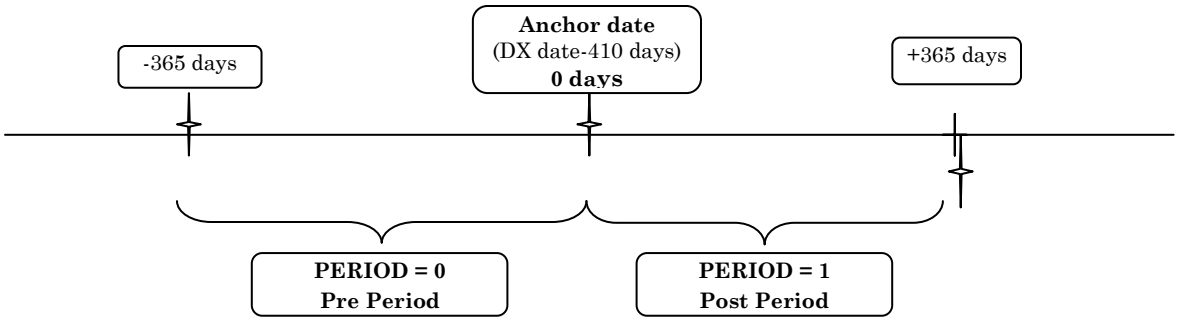


Figure 2.1 (b) Timeline for comparison group

The sample selection process was predetermined. First, a random sample was generated with selection probability of 0.5. The selected sample and the rest of the cases are mutually exclusive. The sample is used as the reference group and the cases not included in the sample are used as treatment group.

Total expenditures for each period for each case were calculated as the summation of all-cause[8] health expenditures from inpatient, outpatient and physician claims. In order to ensure that all claims are included for each patient, full enrollment in the Medicare Part A and Part B was required for the post period for each patient. However, for the pre period, at least 180 days of enrollment was required. However, the expenditures of those having less than full enrollment in the pre period, were prorated for one year period using their available spending. Patients over age 85 or with end stage renal decease were removed from the sample in order to avoid outlying expenditures. Finally, all charges were adjusted for 2005 prices using consumer price index. Here it is important to note that prescription

[8] All-cause health expenditure includes expenses made for all health care services, not only the expenses attributable to prostate cancer treatment

drug expenses or pharmacy claims are not included in the calculation of total expenditures.

After applying all inclusion and exclusion criteria 97,125 cases were selected. The reference group has 49,976 cases, whereas the treatment group for category II has 47,149 cases.

2.4.2 Identification

The identification is based on the assumption that the diagnosis of cancer is randomly assigned irrespective of the past or potential future spending. The quasi experimental analytical sample design ensures the randomness. Further, the panel form of the data helps to minimize the bias arising from the patient characteristics, such as patient level fixed effects. For example, the selection of treatment may be based on the patients' potential spending, such as high cost patient having a systematically different treatment preferences.

2.4.3 Sample Characteristics

Table 2.1 shows patient characteristics in terms of key variables. The summary of sample characteristics is produced for the overall study population who satisfy the inclusion criteria. Those who are not eligible by the inclusion criteria are not included in the table. The classification is made broadly on the basis of diagnosis status. Diagnosed category is our treatment group, whereas undiagnosed category is our comparison group. Summary table is not produced for different

categories and groups mentioned above as it is expected that the distribution of patient population characteristics is not substantially different.

Table 2.1 Sample characteristics by the status of diagnosis (DX)

	Reference group N=49976		**Treatment group** N=47149	
Variables	***Mean***	***Std***	***Mean***	***Std***
Pre Expenditure	$7,880	20506	$9,163	23311
Post Expenditure	$8,642	23054	$42,400	47273
Distribution by year (%)*				
Dx in 1992	1.59%		0.01%	
Dx in 1993	9.36%		5.57%	
Dx in 1994	8.21%		8.48%	
Dx in 1995	7.56%		8.00%	
Dx in 1996	7.07%		7.58%	
Dx in 1997	7.23%		7.79%	
Dx in 1998	7.08%		7.28%	
Dx in 1999	7.52%		8.10%	
Dx in 2000	14.57%		15.54%	
Dx in 2001	14.85%		15.62%	
Dx in 2002	14.96%		16.02%	
Age in years	73.75	5.443	74.02	5.387
Charlson Comorbidity score	2.24	2.013	2.25	2.016
Race: African American	10%	0.298	10%	0.303
Race: Other	7%	0.256	7%	0.256
Metro	58%	0.493	58%	0.494
Therapy Started	n/a	n/a	78%	0.413
College education or higher by zip code	28%	16.94	27.5%	16.88
Mean income by zip code	$50,400	21229	$50,163	21414

*For reference group, anchor date was treated as the date of diagnosis for this purpose.

First two rows report the mean and standard deviation of pre- and post-period expenditures for the treatment and comparison groups. Presumably, the pre-period mean expenditure should not be significantly different for treatment and control groups. However, they appear to be different. There is a valid reason for such a discrepancy. Remember that pre-diagnosis expenditure is one year newer in average for the treatment group. Even though they are discounted by using the CPI, the discounting is not sufficient to make them equal if medical price index rises faster than consumer price index.

No other variables included in the table are noticeably different except for the expenditure variables. The table also lists the distribution of treatment group by year of diagnosis. A larger proportion of the data falls towards the later part of the study period.

2.4.4 Analytical work

Finally, data analysis is carried out in order to estimate the associated spending or cost of the incidence of cancer. The cost associated with each of the categories II, III and IV are estimated vis-à-vis category I as explained above. In order to calculate the cost associated with diagnosis (category II), category II cases were pooled with category I cases. A dichotomous variable (DX=1|0) was created to indicate category II. The variable DX is the main variable of interest here.

Regression using GEE estimation technique was used for the analysis. Two types of estimations are made. First, regression estimation was used in order to adjust for the covariates and calculate trends of expenditures. Next, year specific

effects on cost or spending were estimated running a regression on the model (2-6) specified above.

2.5 Findings

2.5.1 Trends of expenditure by diagnosis status

In this sub-section expenditures of cases in category II defined above are included. Figure 2.2 below shows how the short term incident cost of prostate cancer grew in the study period. The expenditures are plotted in both adjusted and unadjusted forms. The *adjusted* expenditures are found using regression method for age, race, incomes, geographic location and comorbidities. Using the estimates from regression models, expenditures are predicted for each observation. Then predicted expenditures are averaged by year of diagnosis and by treatment or reference group status.

Unadjusted expenditures are calculated as follows. First, the difference of pre and post expenditures (differenced expenditure) for each individual in each of treatment and control group were calculated. Next the difference was averaged for each group and for each year. Finally, the net expenditure was calculated as the difference between annual average differenced expenditure of the control group and annual differenced expenditure for the treatment group.

Figure 2.2 shows that spending associated with the diagnosis of cancer grew continuously throughout the period. The growth became sharp towards the end of the period. It is also evident that the expenditures, in 2005 dollar terms, more than

doubled during the study period. Note that the calculated expenditures are one year cost or spending associated with the diagnosis of prostate cancer irrespective of treatment status.

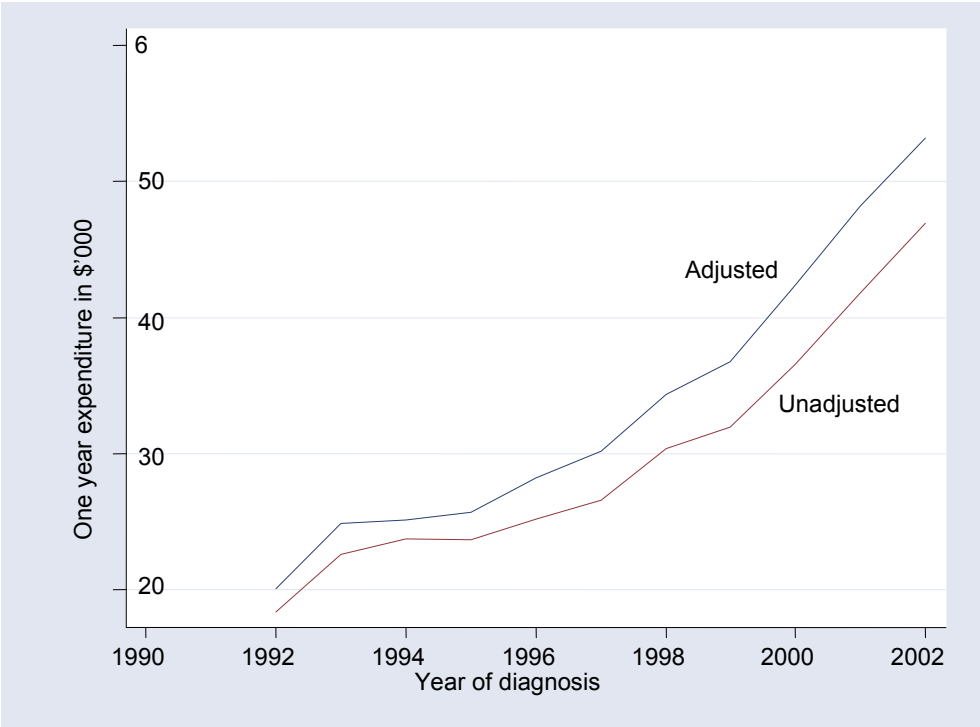


Figure 2.2 Trends of net expenditure by diagnosis

As shown by figure 2.2, the adjusted spending grew slightly faster than unadjusted spending and the gap between the two widened. This indicates that the distribution of covariates among cancer patients have changed over time.

Table 2.2: Estimates of cancer related spending by year of diagnosis

	Estimates by diagnosis status (Dependent Variable = Expenditure)		**Estimates by diagnosis and treatment status** (Dependent Variable = Expenditure)	
Year of diagnosis	Coefficient (Std. Err)	Marginal Effect	Coefficient (Std. Err)	Marginal Effect
1992	0.740* (1.015)	$12,301	0.54* (1.184)	$8,960
1993	1.343 (0.041)	$31,137	1.59 (0.049)	$48,018
1994	1.398 (0.034)	$33,179	1.66 (0.040)	$51,658
1995	1.415 (0.035)	$33,995	1.64 (0.041)	$51,040
1996	1.504 (0.036)	$38,161	1.71 (0.042)	$55,188
1997	1.578 (0.035)	$41,862	1.77 (0.041)	$59,018
1998	1.676 (0.037)	$47,282	1.85 (0.043)	$65,625
1999	1.762 (0.035)	$52,228	1.93 (0.041)	$71,184
2000	1.755 (0.026)	$50,209	1.90 (0.030)	$67,027
2001	1.880 (0.025)	$57,945	2.00 (0.030)	$74,770
2002	2.002 (0.025)	$66,434	2.12 (0.030)	$85,267

*Not significant at 5% level

Note: Estimates of the coefficients on other control variables are not shown

The left half (first three columns) of Table 2.2 shows the estimated results for each year from the regression model (full equation estimates are shown in Appendix A). These are estimates of expenses for the year following diagnosis of the cancer patients who are diagnosed in the particular year. The regression equation included all covariates included in the data summary Table 2.1 except the therapy variable. The regression model also included a full set of place dummies for SEER registry locations. The estimation of coefficients and their implied values (the marginal effect) in dollar terms are also presented. For all years the estimates are significant even below the 1% level. The estimate for 1992 was insignificant. In 2005 dollar terms, people diagnosed with cancer (on average) spent about $66,000 more in 2002 than the similar but cancer free population. This is up from $31,000 in 1993. The spending increment attributable to the diagnosis of cancer more than doubled during that period.

2.5.2 Trends of expenditure by diagnosis and treatment status

Most prostate cancer patients receive some sort of treatment within 4 months of diagnosis. Not everyone diagnosed with prostate cancer receives treatment immediately. Treatment decisions are based on the expected outcomes for the patient depending on several factors including patient's expected life, health condition, and stage of cancer. Those who do not receive treatment are kept under watchful waiting for any change in cancer behavior. It must be noted that those who do not receive a definitive treatment, either surgery or radiation therapy, may receive other less intensive treatment such as hormonal therapy. Hormonal therapy

given prior to a definitive treatment is called neo-adjuvant therapy. Those who have more advanced form of cancer may be given a palliative care that includes hormonal and other therapies.

Presumably, patients not receiving a definitive therapy have lower spending. However, since our expenses include "all-cause" expenditures, this may create an illusory situation. People who do not receive treatment because of health and life expectancy reasons may have other significant expenses causing the overall expenditures to be high. But there might be some people who are otherwise healthy but do not receive an immediate treatment because their cancer is less threatening. Creating a sub-sample of individuals who do not receive a treatment leaves us with a more homogenous cohorts of people that will allow us to estimate the treatment expenses more precisely.

The subsample used in this subsection includes all category III patients described above as treatment group. Those who do not receive any of the radiation or surgery treatments in the post-period are discarded. The reference group remains the same.

The trends of net expenditures by diagnosis and treatment status are shown in Figure 2.3. Expenditures are relatively stable until 1995 and then they have sharper increase. Both adjusted and unadjusted expenditures have similar trends.

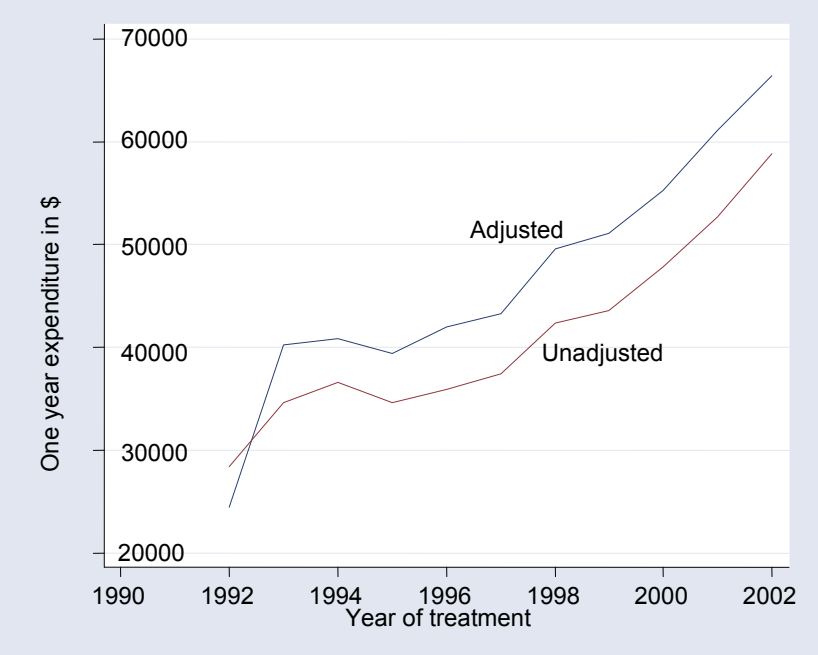


Figure 2.3 Trends of net expenditure by diagnosis and treatment status

The right two columns of Table 2.2 show the estimated results of year effect. The estimated coefficients are highly significant except that for year 1992. The exponentiated linear prediction of the estimated values shows the marginal effect of the treatment group in dollar terms. Comparing the dollar expenditures of treated subsample with that of diagnosed subsample shows that the levels of expenditure for treated subsample is significantly higher than that of diagnosed albeit they have slower growth rate. From 1993 to 2002, the expenditure for treated group grew almost by 80 percent in 2005 dollar terms.

2.5.3 Trends by treatment types:

For this section, category IV patients are used as treatment group, which are divided into three groups:

Group I: Those who received surgery within 4 months of diagnosis

Group II: Those who received radiation therapy within 4 months of diagnosis

Group III: Those who received none of radiation therapy or surgery during the post period. This group is named as 'no treatment' group.

The trend of expenditure for each treatment type is estimated separately and their adjusted expenditures are presented in figure 2.4 below. Unlike the above two, the unadjusted expenditure trends are not shown for these groups. Also, the trends are plotted using Lowess plots which will smooth out the trends and allow an easy comparison.

It is evident that the trend of expenditure of the radiation group is similar to that of 'no treatment' group but with a higher intercept. The radiation group shows a slight fall in spending during the first half of the overall period, whereas no treatment group shows a moderate rise in the same period. Both radiation and no treatment group have relatively flat part in the middle of the study period. However, during the second half of the study period, spending for both of these two groups show a fairly noticeable and similar growing trend.

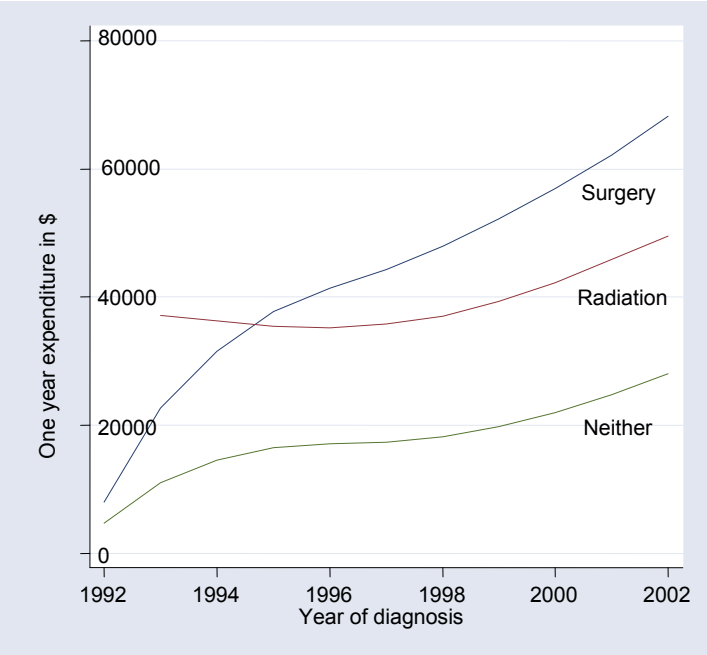


Figure 2.4 Lowess plots of expenditures by treatment type

The expenditure trend of radical prostatectomy is very different. It grows continuously from the beginning to the end. This signifies substantial changes in surgery treatment as opposed to radiation or other treatment option.

2.6 Discussion and conclusion

The main purpose of this chapter is to get a general sense of how the expenditures associated with the prostate cancer behaved over time. Without pinpointing a particular aspect and doing a complex analysis, the database is

allowed to speak for itself. The observations made from the data are interesting and have important interpretations.

Trends of expenditure were calculated and plotted in order to obtain a growth picture of health care spending for cancer care over the period. These trends provided a simple picture that is easily understandable just by eyeballing the trends. No special statistical tests were conducted to make inferences about the differences because the changes were fairly substantial and obvious.

Results show that the health care spending for cancer care has increased substantially during the study period. People diagnosed with cancer have utilized health services at increasing rate over time implying the significant changes in the way cancer care is delivered. The care has become increasingly more resource intensive. Assuming that the prices of health care inputs used provide care for cancer patients did not change at different rate than the price of the rest of the inputs, this implies technological change in cancer care demands more resources. The results suggest that technological change specific to PCa alone contributes about 100 percent increase in health care spending in about 10 years' period. This also implies that technological advancement caused the PCa care expenditure to grow at the exponential rate of 7 percent each year during that period.

The findings reject the hypothesis that people diagnosed with cancer do not have substantially different expenditure than those without cancer in the favor for the alternative hypothesis.

The trends of expenditures for diagnosed population and treated population also show some differences. The treated expenditures did not rise sharply during the early stage of study period. However, they have similar trend towards the end of the study period. The finding suggests that innovations in major treatment alone caused PCa care expenditure to grow by 80 percent. The hypothesis of no difference in expenditure between the diagnosed and treated group is rejected in the favor of alternative one.

Comparison of expenditure growth by the method of treatment exemplifies the differences. Expenditures for surgery patients grew much faster over the entire period. Radiation group and no treatment group show only a moderate increase in spending during the second half of the study period. It implies significant changes in the treatment methods for those who receive surgery as their definitive treatment. This also suggests the changes in radiation treatment and other care after 1998. This again rejects the null hypothesis that the trends of expenditure for different methods of treatment are the same, in the favor of alternative one. Instead the alternative hypothesis that the growth trend in total health care expenditure in people *treated* for cancer with different methods is *different* from those without cancer in the study period has been accepted.

Estimated cost can also be used to evaluate the population based cost-effectiveness of technological advancement in PCa care. From 1993 to 2002, the average age of people dying of PCa increased from 78.81 years to 80.46 years in the SEER-

Medicare population[9]. This is a gain of 1.65 life years in average. Using the cost estimates, it implies that the cost for per life year gained is little more than $20,000. However, it is only the first year cost. Advances in prostate cancer care appear to be highly cost effective as costs for subsequent years are not substantial for most patients.

[9] Calculated from the 1991-2002 SEER data.

CHAPTER 3

USING A SINGLE MEASURE OF TECHNOLOGY

3.1 Introduction

In this chapter, I seek the answer to the question: What is the effect of overall technological change on overall healthcare spending? The specific aim of this chapter is to construct and use a measure of overall technological change in prostate cancer care and measure the association between the measure of technology and short-term incidence cost of prostate cancer. In accordance with the specific aim III of this research presented in Chapter 1, the study hypothesis for this chapter is stated as follows.

Hypothesis: For all individuals diagnosed with prostate cancer:

H0.3: There is *no* significant association between technology index and total PCa care expenditure in the study period.

H1.3: There is significant association between technology index and total PCa care expenditure in the study period.

In order to be able to test this hypothesis, two key variables, technology and health care expenditure, are needed. This section, therefore, implicitly assumes that 'technology' has some sort of measurement. In cross sectional terms, the amount of technology used to provide care to one person could differ from that of another person. If two persons are comparable in every other possible sense, the varying the amount of technology used to provide care may vary health outcome and therefore

health care expenditure between two persons. Here the outcome of interest is expenditure.

How to construct a single measure of technology embodied with thousands of possible inputs that go in the care is a critical question. However, without a single measure of technology, it is impossible to find the answer to the research question for this chapter.

Since constructing an objective measure of health care technology for a particular time is a difficult task, and therefore beyond the scope of this research, I used an alternative approach. The alternative is to look for any proxy that can most properly represent the measure of technology. This is based on an assumption that technological change always brings some improvement in outcomes. In other words, improvement in outcomes is 'caused' by technological change. This means technological change is properly represented by the change in outcomes in the long run.

My strategy is to use outcome as a proxy variable for technological change. There can be different outcomes as candidates for this purpose. One such measure can be provided by the survival rate following the diagnosis of prostate cancer. The survival rate can be used for a particular time frame, such as three year, five year or ten year survival rate following the diagnosis. The survival rate is a measure of how many people were alive within the time frame per 100 people diagnosed with that condition.

The second alternative is death rate owing to prostate cancer. Prostate cancer is still one of the leading causes of deaths among men in the US. The leading causes of death statistics, which measure how many of deaths per 100,000 population are attributed to various conditions, are available from secondary sources. Assuming constant incidence and prevalence rates, a falling prostate cancer death rate means that less people die of prostate cancer. But death is inevitable and everybody eventually dies of a certain 'cause'. A falling death rate caused by prostate cancer means more people are dying of other conditions. The cause of death is, therefore, only a relative measure of technological change which shows a relative progress in the cure and care of prostate cancer or cancer care in general.

Both measures have their own limitations as measures of technological progress. Survival rate is highly sensitive to stage at diagnosis of cancer which is difficult to adjust. Due to increased usage of screening and health care awareness, more and more prostate cancers are detected in their early stage and early age of patients. This will affect the survival rate even without any change in the treatment and care of prostate cancer. The second measure, death rate owing to prostate cancer, as a proxy for technological change is a better alternative in this regard. There are limitations of death rates as a measure of outcome. One important limitation is that death information is obtained from death certificates, which do not accurately report the cause of death. However, I would argue in favor of this because it is more specific and measurable.

3.2 Theoretical Construct

The primarily link between the technological change in health care and expenditure is given by the amount of resources that go into the care. In other words, technological change can lead to change in the types or amounts of inputs used to provide the care. Every technological change will need some change in inputs: either there are new inputs, more or less of existing inputs, a new mix of existing inputs, or a mix of new and existing inputs.

A new technology is acceptable only when the net utility[10] from it is at least as high as that from existing technology. This ensures that health outcomes are non-decreasing function of technological change. In other words,

$$U(d_i) \geq U(d_j) \qquad (1)$$

for any technology $i \neq j$. Here d denotes a vector of inputs associated with the technology. Let d_i^* be an objective measure of technology for input mix i. Then above condition implies that $d_i^* \geq d_j^*$. Let us also define a functional relationship between the input mixes and associated measure of technology as

$$d_i^* = g(d_i) \qquad (2)$$

However health utility is not directly observed. What we observe is health outcome. Let us assume that there is a direct mapping of health technology with health utility and the mapping is properly defined. In other words, health outcome directly varies with health technology given as:

[10] It may be defined as the marginal utility net of marginal cost of a new technology

$$H_i(d_i^*) = f(X, d_i^*, \gamma) \qquad (3)$$

where, γ is a vector of parameters and, X is a vector of patient characteristics. Assuming the continuity of d^*, it further implies that

$$\frac{\partial H(d^*)}{\partial t} = \frac{\partial f(X, d^*, \gamma)}{\partial d^*} \frac{\partial d^*}{\partial t} \geq 0$$

where $\frac{\partial d_i^*}{\partial t} \geq 0$ and it implies that technology is a non-decreasing function of time.

Similarly, health expenditure is a function of inputs that go into care.

$$E(d_i^*) = g(X, d_i^*, \delta) \qquad (4)$$

$$\frac{\partial E}{\partial t} = \frac{\partial g(X, d_i, \delta)}{\partial d_i} \frac{\partial d_i}{\partial d^*} \frac{\partial d^*}{\partial t}$$

Again, $\frac{\partial d_i^*}{\partial t} \geq 0$ and $\frac{\partial g(X, d_i, \delta)}{\partial d_i} \geq 0$, but the sign of the derivative $\frac{\partial d_i}{\partial d^*}$ is unknown. It implies that health expenditure can increase or decrease over time depending on the resource intensity of new technologies. Equations (3) and (4) provide the basic building blocks for the theoretical background for this chapter.

3.3 Empirical Strategy

The empirical problem of this chapter is to estimate the equation

$$E = g(X, d_i, \delta), \qquad (5)$$

and the main interest of this research is to measure $\frac{\partial E}{\partial d^*}$. However, in order to make it estimable, we need to make some further assumptions. First, we need to make assumption about the functional form of the equation. Second, we need to use a proxy variable for d^*since the objective measure of $d^*$is not available.

The expenditure function is assumed to be non-linear with an additively separable assumption for the covariates on the right hand side. So the regression model for the expenditure equation is in the form

$$g^{-1}(E) = \sum_{i=1}^{k}(\boldsymbol{X_k\delta}) + \theta d^* + \varepsilon \qquad (6)$$

I use the outcome itself as a proxy for $d^*$for this purpose. Controlling for patient characteristics, health outcome, $H(d^*)$, gives the weighted measure of technological change.

Here two strong assumptions are made:

Assumption 1 *(Causality)*

An improvement in outcome must be due to a change in inputs or input mix which is broadly defined as technological change in health care. The reverse causality that more expenditure improves outcome is ruled out implying that outcome is not endogenous in the model.

This assumption can be justified in health care setting where improving the outcome is of major concern for both patients and providers. There is a negligible marginal cost to patients for choosing the treatments that are safer and more effective. Because of third party payment, expected outcome rather than expected cost, plays the role while choosing a treatment. So the choice of treatment method is independent of expected expenditure. If a technologically more advanced option of treatment is chosen, it may be reflected in the outcome. The outcome even includes

the technological improvement through learning by doing. Therefore, outcome is a weighted measure of all improvements made in the care.

Under the assumption of causality, a single equation non-linear regression technique with continuous outcome variable on the right hand side is used to measure the effect of technological change in cancer care expenditure. Generalized linear model (GLM) estimation technique[11] is used in the analysis.

The assumption of causality may seem too strong in this case. If the assumption fails, the estimation based on the assumption will be biased. In order to accommodate the possibility of endogeneity, the following assumption is made.

Assumption 2 (*Simultaneity)*

Expenditure and outcome are simultaneously determined. So the outcome is endogenous in the expenditure model. This assumption allows for the possibility that expenditure has an impact on the outcome.

As explained above, health outcome correctly reflects the use of technology which in turn determines the amount and type of inputs used. Expenditure depends on the amount and types of inputs used.

[11] This method is discussed in Chapter 2.

3.4 Empirical model

I use simultaneous equation modeling[12] to estimate the relationship. Let us assume that there are G endogenous variables in the system of equations. The Gth equation for ith of N individuals is written as

$$y_{ig} = z_{ig}^{'}\gamma_{ig} + Y_{ig}^{'}\beta_g + u_{ig} \qquad g = 1, 2, \dots G \qquad (7)$$

where, z is a vector of exogenous variables and Y is a vector of $(G-1)$ endogenous variables. Equation (5) is a structural form of G equation linear simultaneous equation model. The $1 \times M$vector of all exogenous variables $\boldsymbol{z}$ is assumed to satisfy

$$E(\boldsymbol{z}^{'}u_g) = 0, \qquad g = 1,2, \dots, G \qquad (8)$$

The empirical strategy is to estimate equations (3) and (4) simultaneously treating the health outcome and expenditures variables as endogenous to the model.

The structural parameters of the model can be consistently estimated if the rank and order conditions for identification are satisfied. The order condition requires that the number of excluded exogenous variables from the equation must be at least as large as the number of included right-hand-side endogenous variables in the equation. This requirement, also known as the order condition with exclusion restrictions, is the necessary condition for identification.

The rank condition of identification depends on linear restrictions and normalization restrictions on an endogenous variable. We need some background information before we can state the rank condition for identification. Let rewrite the system of linear equations (7) compactly as

[12] The theoretical model for this part is heavily drawn from Wooldridge (2002), Cameron and Trivedi (2006) and Green (2004).

$$\boldsymbol{yB} = \boldsymbol{z\Gamma} + \boldsymbol{u} \qquad (8)$$

where, $\boldsymbol{u}$ is a $1 \times G$ vector of structural errors, $\boldsymbol{\Gamma}$ is a $\boldsymbol{M} \times \boldsymbol{G}$ matrix and $\boldsymbol{\Gamma}$ **is** $G \times G$matrix.

For all Gequations of a structural model, we can solve it in terms of exogenous variables and obtain a reduced form equation as

$$\mathbf{y}_{\mathrm{i}} = \mathbf{z\Gamma B^{-1}} + \mathbf{uB^{-1}} = \mathbf{z\Pi} + \mathbf{v} \qquad (9)$$

where, $\boldsymbol{\Pi} \equiv \boldsymbol{\Gamma B^{-1}}$ **and** $\boldsymbol{v} = \mathbf{uB^{-1}}$. The rearrangement is based on the assumption that the matrix $\mathbf{B}$ is non-singular and the variance matrix $\mathbf{E(u'u)}$ is also non-singular. **Let** $\Delta \equiv \begin{pmatrix} \boldsymbol{B} \\ \boldsymbol{\Gamma} \end{pmatrix}$ be the $(\mathrm{G} + \mathrm{M}) \times \mathrm{G}$ matrix of structural parameters in equation (8). Let $\boldsymbol{\beta}_1$ be the $(\mathrm{G} + \mathrm{M}) \times 1$ vector of structural parameters in the first equation (7). One element in the coefficient vector of endogenous variable in (7) is set to -1 as a normalization restriction so that there are $(\mathrm{G} + \mathrm{M}) - 1$ unknown elements in $\boldsymbol{\beta}_1$. Assume that prior knowledge of $\boldsymbol{\beta}_1$ can be expressed as

$$\mathbf{R_1\beta_1} = \mathbf{0}$$

where, $\mathbf{R_1}$is a $(\mathrm{G} + \mathrm{M}) \times \mathrm{J}$ matrix of known constants J is the number of restriction on $\boldsymbol{\beta}_1$.

The rank condition requires that $\boldsymbol{\beta}_1$is identified if and only if the rank condition rank $\mathbf{R_1\beta_1} = \mathrm{G} - 1$ holds**.**

3.4 Empirical analysis

3.4.1 Sampling design and key variables

The analytical sample used in this chapter includes all patients diagnosed with prostate cancer from 1991 to 2002. Only the patients who were continuously eligible for Part A and B of Medicare coverage were selected. The date prior to 45 days of date of diagnosis was created for each case as an anchor date. Then aggregate expenditures were calculated for the period of 365 days from the anchor date. The aggregate expenditure includes all the claims for inpatient, outpatient and physician services.

Compared to the sample design of Chapter 2, the sample used in this chapter is different in a number of ways. First, this sample does not include comparison and treatment groups. Second, this sample does not include the expenditure of the previous period. Third, everyone in the sample has full expenditure information for one year. So no adjustment was needed for anyone having less than a full period's expenditure.

Patients aged over age 85, or with end stage renal disease were removed from the sample in order to avoid outlying values of expenditure. Finally, all charges were adjusted for 2005 prices using the general consumer price index (CPI).

3.4.2 Identification

As explained above, the identification is based on the rank and order conditions. The satisfaction of the rank condition is easy to see as the model has only two endogenous variables. To satisfy the order condition, I have used inclusion

and exclusion criteria in the equations. In the equation that determines health outcomes, I have used the year dummies in which the patient was diagnosed with cancer. It makes sense because the outcomes are clearly time-dependent, a patient diagnosed with cancer in 2002 is more likely to have better survival outcome than a patient diagnosed in 1991.

Once we include the outcome variable in the expenditure equation, the year of diagnosis becomes purely redundant as all information is contained by the outcome variable. The assumption of this study is that outcome is the index of the technology of care that summarizes all the changes in the method of care brought by technological change. Therefore, we can exclude the time of diagnosis information from the expenditure equation.

At least one variable which is in the expenditure equation needs to be excluded from outcome equation. I have excluded the variable that indicates whether patients were given one of the definitive therapies within 4 months of diagnosis. The therapy variable causes expenditure to increase but it is not assumed to have any relevance in the outcome equation. Conceptually, the outcome is the function of the overall level of technology of any time and the year of diagnosis fully incorporates that information. So, the indicator for the definitive therapy is purely redundant in the outcome equation given the presence of diagnosis years.

3.4.3 Three Stage Least Square (3SLS) Approach

In simultaneous equation model (SEM), I use the three-stage least square (3SLS) approach to estimate the equations. Unlike the two-stage equation by equation estimation of the model, 3SLS assumes errors are homoskedastic but are correlated across equations in order to ensure consistency in the estimates.

3.4.4 Summary of key variables

Table 3.1 (*a* and *b*) shows the summary statistics of the key variables included in the empirical estimation equations. The key variables also include death rates associated with prostate cancer in the year. Information of death rates is obtained from NCI database and other published reports. It is important to note that there is a significant lag between the outcome (death rate in this regard) and PCa care following the diagnosis. While patients receive care right from the date of diagnosis, the eventual survival or death from the disease occurs after several years in average. So the death rate in the year of diagnosis provides little information about the type of care these patients receive that affects their ultimate survival. For this reason, I have used outcome variables that are constructed by leading the outcome variable by one, two, three, four and five years following the diagnosis[13]. The death rate with five year lead means that outcomes after five years are more associated with the type of care the patients receive today right after they are diagnosed.

[13] For example a five year lead value means using the death rate of 2005 for the patients diagnosed in 2001.

Table 3.1 (a) shows the death rate due to prostate cancer by year with rates led by one, two, three, four and five years. It also shows the five year moving average rate. All the rates are in terms of every 100,000 population aged 65 or above. In 1991, the death rate was 291.08 while it decreased to 209.67 in 2002. In 2006, which is five years after 2002, the rate was reduced to 173.56.

Table 3.1 (a): Death rates owing to prostate cancer in every 100,000 male population aged 65 or above by year and their lead and moving average values

	Year 1	**Year 2**	**Year 3**	**Year 4**	**Year 5**	**Moving Average**
1991	291.08	290.58	292.48	286.48	277.23	287.57
1992	290.58	292.48	286.48	277.23	267.61	282.88
1993	292.48	286.48	277.23	267.61	254.26	275.61
1994	286.48	277.23	267.61	254.26	242.49	265.61
1995	277.23	267.61	254.26	242.49	235.48	255.41
1996	267.61	254.26	242.49	235.48	226.13	245.19
1997	254.26	242.49	235.48	226.13	217.38	235.15
1998	242.49	235.48	226.13	217.38	209.67	226.23
1999	235.48	226.13	217.38	209.67	197.00	217.13
2000	226.13	217.38	209.67	197.00	189.20	207.88
2001	217.38	209.67	197.00	189.20	182.92	199.23
2002	209.67	197.00	189.20	182.92	173.56	190.47
Average	**257.57**	**249.73**	**241.28**	**232.15**	**222.74**	**240.69**
Std. Dev.	30.72	33.29	34.81	34.53	33.76	33.26

Including the average death rate during five years following the year of diagnosis makes six outcome variables. The most appropriate outcome for the analysis is death rate after five years. Although outcome after five years looks most reasonable, we cannot rule out the survival rate of one, two, three and four year apart as they may have some information about the state of technology in that year.

The next appropriate outcome variable could be the average rate from one to five years.

Table 3.1 (b) shows the summary statistics of other covariates included in the analysis. As the table shows, the average pre diagnosis expenditure was $10,039 which increased to $47,061 in the post diagnosis period. The mean age at diagnosis is slightly more than 73 years. We need to remember that it is the mean age of diagnosis only among the study populations who are 65 years or older.

Table 3.1 (b): Summary Statistics of some key variables
N=120816

	Summary Statistics	
Variables	***Statistic***	***Std. Dev.***
Mean pre Expenditure	$10,039	26476
Mean Post Expenditure	$47,061	47844
Mean of difference between pre and post expenditure	$37,021	50999
Mean age in years	73.27	5.58
Mean of Charlson Comorbidity score	2.25	2.02
Race: White	83%	0.37*
Race: African American	10%	0.30*
Race: Other	7%	0.25*
Metastatic	4%	0.19*
Unstaged	7%	0.26*
Residence in metropolitan areas	59%	0.49*
Therapy Started	81%	0.39*
Mean of college education or higher by zip code	28%	17.03
Mean income by zip code	$50,654	21340

Notes: * Standard deviations are calculated in terms of proportions, not in percentage

Charlson's comorbidity score shows the comorbid conditions that provide information about the distributions of pre-existing conditions among patients

affecting total health care expenditure for them. The distribution of race is a little different from what the overall US population looks like. The percentage of white population is slightly larger compared to the overall population distribution[14]. However, even though the incidence is higher in the Black population[15], the data show a smaller representation of Blacks compared to their overall population share (12.3%). A substantial population lives in big cities given by metro locations (59%).

Table 3.1 (c) Mean expenditure by year of diagnosis

Year	N Obs. (%) Total N = 120,816	Pre Expenditure		Post Expenditure		Differenced Exp.	
		Mean $	Std Dev	Mean $	Std Dev	Mean $	Std Dev
1991	3,279 (2.71)	10582	30604	42340	40575	31757	47346
1992	12,299 (10.18)	9056	22216	40069	37959	31012	41339
1993	10,594 (8.77)	8567	21050	38797	39768	30230	41809
1994	8,875 (7.35)	8322	20754	38735	41654	30413	44221
1995	8,020 (6.64)	8231	19737	37788	43362	29557	45418
1996	7,449 (6.17)	8700	22188	39322	36534	30622	39707
1997	7,689 (6.36)	8629	24610	41004	37446	32375	41878
1998	7,233 (5.99)	9513	27503	45347	42184	35834	45435
1999	7,872 (6.52)	9431	22761	46119	40715	36688	42980
2000	15,317 (12.68)	11016	28452	51088	46968	40072	51225
2001	15,845 (13.11)	11478	29503	57071	58012	45593	61184
2002	16344 (13.53)	12939	34584	61810	62391	48871	66978

[14] According to the US Census Bureau, Whites, Blacks and Hispanic and Asian population were 75.1%, 12.3%, 12.5% and 3.5% respectively as of year 2000. (Source: http://factfinder.census.gov/servlet/SAFFFacts).
[15] Source Central for Disease Control (CDC) website (http://www.cdc.gov/cancer/prostate/statistics/race.htm).

The table also provides information about the stage of cancer at diagnosis. Only the malignant and unknown stages are included in the analysis as they are assumed to have a significant impact on the spending. Among all diagnosed with cancer, 81% of them start therapy within one year of diagnosis.

SEER does not provide individual level information on income and education. These information are available only through external sources such as census tracts. The database has zip code level information on income and education. The mean of zip code level mean income was $50,654 and mean of percentage of individuals with college or higher degree in zip code level was 28% in the sample.

Table 3.1 (c) shows mean expenditures by year of diagnosis. Both pre and post diagnosis expenditure show similar trend—the post expenditure fall until 1995 and then start rising again. The pre-expenditures fall further until 1996 before they start rising. The differenced expenditures have the same trend as post expenditure. The total growth of pre expenditure was 22 percent over the entire period 1991-2002. However, the post expenditure grew by 46 percent during the same period. The differenced expenditure grew by the largest percentage, i.e. 54 percent during that period.

It is assumed that the differenced expenditure is the expenditure attributable to the diagnosis of cancer. The growth rate of 54 percent, which is net of regular growth in spending, is supposedly caused by advances in the care of prostate cancer.

Table 3.1 (d) Distribution of sample and expenditures by SEER registry locations				
SEER Registry Locations	**N Obs (%)**	**Variables**	**Mean $**	**Std Dev**
02=Connecticut	11769 (9.7)	Pre Expenditure Post Expenditure Diff Expenditure	8594 43230 34636	24013 37679 42836
20 = Detroit	19116 (15.8)	Pre Expenditure Post Expenditure Diff Expenditure	10579 53918 43339	21534 43577 46217
21 = Hawaii	2503 (2.1)	Pre Expenditure Post Expenditure Diff Expenditure	7210 43945 36736	18092 36798 39528
22 = Iowa	12645 (10.5)	Pre Expenditure Post Expenditure Diff Expenditure	6328 29643 23315	15745 28203 30645
23 = New Mexico	4698 (3.9)	Pre Expenditure Post Expenditure Diff Expenditure	6931 35118 28187	18546 37201 39657
25 = Seattle	9791 (8.1)	Pre Expenditure Post Expenditure Diff Expenditure	6095 32671 26575	14167 27602 29779
26 = Utah	5886 (4.9)	Pre Expenditure Post Expenditure Diff Expenditure	6331 28288 21957	15289 26602 29771
27 = Atlanta metropolitan	5600 (4.6)	Pre Expenditure Post Expenditure Diff Expenditure	8045 43314 35269	17303 32095 34446
37 = Rural Georgia	404 (0.3)	Pre Expenditure Post Expenditure Diff Expenditure	8206 39754 31547	16302 33596 36189
42 = Kentucky	3848 (3.2)	Pre Expenditure Post Expenditure Diff Expenditure	9193 44353 35160	19210 35033 38288
43 = Louisiana	3492 (2.9)	Pre Expenditure Post Expenditure Diff Expenditure	13079 49291 36213	27632 45177 49106
44 = New Jersey	8863 (7.3)	Pre Expenditure Post Expenditure Diff Expenditure	14136 69351 55215	37202 69696 73836
88 = California	32201 (26.6)	Pre Expenditure Post Expenditure Diff Expenditure	13271 55713 42442	35664 59554 64820

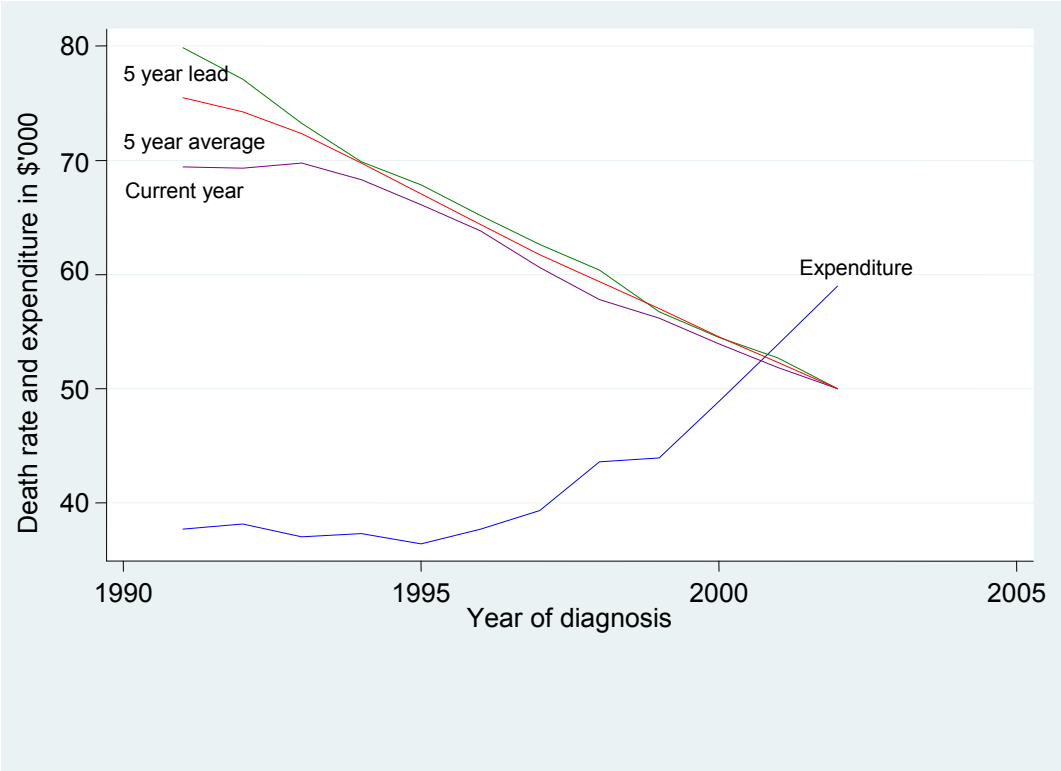


Figure 3.1 Trends of PCa caused death rate and one year health expenditure from 1991 to 2002

Finally, Table 3.1 (d) shows mean expenditure and frequency distribution by SEER locations. Note that in regression equations, a full set of SEER location dummies are used.

Figure 3.1 shows the visual picture of the expenditures and outcome variables over the study period. Only three outcome variables and one expenditure variable are used in the figure for comparison. In order to make comparison easier, the latest value of each outcome variable was fixed at 50 and all previous years' values were adjusted accordingly.

The current death rate is stable to begin with and starts falling from year 1994. The death rate after five years is falling throughout. The average death rate is somewhere in between the two other. The health outcome is continuously improving over time. However, the expenditure trend is somewhat different. It is stable or slightly falling until 1995 after which is shows a rising trend. The trend of expenditure is sharp particularly after 1999.

3.5 Results

The results from single equation estimation and simultaneous equation estimation are obtained. Table 3.2 shows the results from single equation model using the non-linear technique. The results for each variable are obtained from separate equation, so the table shows results from six estimating equations. The left hand side variable is the differenced expenditure and the variable of interest on the right hand side is death rate. Each equation included a set of control variables that included patients' age, race, comorbidity, treatment status, stage of cancer, dummy for metro residence, and full set of dummy variables for geographic locations defined by SEER registries. Full equation estimates are shown in Appendix B.

All coefficients of interest are highly significant. The first year outcome has the highest association with expenditure and fourth year outcome has the lowest. It shows that increasing the gap between diagnosis year and outcome year continuously lowers the magnitude of impact until year four. The fifth year

outcome, however, has a larger impact even that of third year. Predictably, the average of outcomes from year one to year five has a moderate impact on spending.

Table 3.2: Results from single equation model
Dependent variable: One year expenditure following diagnosis

Variables of interest	Coefficient	Standard Error	z-statistic	P > |z|	Implied marginal effect (in $)
First year	-0.0059	0.000155	-38.20	0.00	-201
Second year	-0.0053	0.000142	-37.46	0.00	-181
Third year	-0.0050	0.000138	-36.99	0.00	-173
Fourth year	-0.0051	0.000141	-36.48	0.00	-174
Fifth year	-0.0053	0.000144	-36.54	0.00	-179
Average (first-fifth year)	-0.0054	0.000144	-37.25	0.00	-183

Since the coefficients of estimation are from a non-linear model with log transformation, a proper interpretation of those results needs to transform them in dollar term. The implied marginal impacts are also calculated in the dollar term and put in the last column. The marginal effects in dollar terms show that a unit reduction in the current year death rate causes the average one year post diagnosis expenditure to go up by $201. The result for 5 year after diagnosis is $179 and average for year 1 through year 5 is $183.

Table 3.3 shows the results from simultaneous equation model. The variables of interest are the same as in the single equation model. The control variables are the same with the modifications explained in the issue of identification above. To keep the table simple, the estimates for control variables are not reported in the table (full equation estimates are shown in Appendix B).

Table 3.3: Results from simultaneous equation model				
Variables of interest	**Coefficient**	**Standard Error**	**z-statistic**	**P>z**
First year	-206	5.37	-38.35	0.00
Second year	-186	4.95	-37.58	0.00
Third year	-179	4.83	-37.10	0.00
Fourth year	-180	4.93	-36.42	0.00
Fifth year	-185	5.07	-36.50	0.00
Average (first-fifth year)	-188	5.04	-37.31	0.00

All coefficients are statistically and economically significant. The current year outcome has the highest impact on spending while the outcomes resulting in four years have the lowest impact. In dollar terms they are -206 and -180 dollars respectively. Note that the estimated coefficients are in dollar terms now and there is no need of conversion as in the single equation model. The coefficient on fifth year outcome (-$185) is slightly larger than that of the third year outcome (-$179). The coefficient on five year moving average is -$188.

We need to carefully interpret the results from single equation and simultaneous equation models in order to get meaningful economic implications. The main explanatory variable of interest was the index of technology proxied by an outcome that closely indicates advances in cancer care. The death rate associated with prostate cancer has been consistently decreasing. Table 3.1 (a) above shows the annual death statistics. The death rate resulting from PCa for 65+ age group

decreased by 103 points from 277 in 1991 to 174 in 2002 in every 100,000 male population. If we take a moderate estimate of $185 as marginal spending, the total spending per patient would be $19,055 for this whole achievement. It means that to bring down the death rate from 277 to 174, per patient first year spending increased by $19,055 in average[16] (assuming linearity).

More interest lies in the cost of one PCa death avoided. During that period, the cancer incidence rate was about 1,000 in seniors aged 65 or above in the same 100,000 population (NCI, 2010). The estimated moderate cost of reducing the death by one point is $185 spent per patient in the first year. There are 1000 new patients in the population pool. It means if $185 more is spent on each incident case in the first year, one less person will die of cancer. So one PCa death avoided is calculated as 1000 times 185, which is $185,000. Using the same $185 rate, the total cost of avoiding one death due to prostate cancer is $185,000 in the 65 and plus population. This is however, only the first year incremental spending not the total cost of avoiding one PCa death. Because most PCa patients get most intensive treatment within a year of diagnosis, $185,000 is the very large chunk of lifetime total spending.

3.6 Discussion and conclusion

The health care expenditure of prostate cancer patients has increased by 54 percent from 1991 to 2002. The average annual growth rate[17] during that time is

[16] This is simply calculated by multiplying the marginal cost of per unit reduction ($185) with total reduction (103).
[17] It is also known as exponential growth rate.

about 3.9%. The causes underlying this growth can be many. However the role of technological change has a significant impact in this long run growth of spending.

How much of this change is attributable to overall technological change is the main research question for this chapter. Finding the answer to this question is possible if we can measure the technology. An objective measure of technology in health care is not available, and no such attempt has been made in health economics literature. It is also beyond the scope of present research.

I have proposed and used a proxy measure of technology given by health care outcomes. These proxy measures are based on the assumption that any long term improvement in health care outcome results only when we have a better knowledge of medicine. This is also known as technological improvement. So, technological change is defined as any change in the practice of medicine that brings improved outcomes for the patients.

We also need to remember that all changes that become the part of technological changes are not equally important. Some are more important than others. Using the outcome as a measure of technological change duly weights all the changes in the measure of technology. Changes that are more effective are given more weights meaning a faster growth of technology in health care.

Two most feasible candidates that provide suitable measure of technological change in health in prostate cancer care include post diagnosis survival rate and the rate of prostate cancer related deaths. Both measures have their own strengths and weaknesses. However, I found that death rates related to prostate cancer comprised

a simpler and more easily available measure of technological progress in prostate cancer care.

Using the health outcome as a measure of technological change invites questions from the standpoint of estimation. Two important assumptions are made in order to provide the basis of analytical design for this chapter. The first assumption is no reverse causality from expenditure to outcome. It means that expenditure cannot affect potential outcome. The second assumption allows the outcome and expenditure to be simultaneously determined. For the first assumption, a single equation non-linear regression model is used in estimation, whereas for the second assumption, a two equation simultaneous equation model is used for estimation.

The results show that outcome alone explains more than $19,000 increase in health care spending due to technological change during that period. Using the population level statistics, the first year cost of one death avoided due to prostate cancer is $185,000 for the study period. These numbers make more sense if we know about the average life expectancy of people diagnosed with prostate cancer in 65 or above age group.

Additional conclusions can be made about the cost effectiveness of the technological change. The average age at diagnosis of PCa was 75 years[18] in the study period. The average life expectancy of male aged 75 years was 84.39 in 1991 and 85.7 years in 2002[19]. This implies that avoiding a death from PCa gave about 7

[18] Calculated from the SEER data.
[19] These data are available from the Actuarial Life Tables by Social Security Administration.

additional life years in the period. The first year cost of additional life year from this perspective is about $26,000.

CHAPTER 4

MEASURING THE IMPACT OF SELECTED TECHNOLOGIES

4.1 Introduction

There are two questions in the relationship between new technologies and health care expenditure or cost that draw specific interest. First, what is the extent to which the increased expenditure is associated with the technological change at both aggregate and disaggregate levels? In the aggregate level, the interest lies in the impact on expenditure of overall technological change in medicine. In the disaggregate level, this question amounts to measuring the incremental cost of a specific technology with or without respect to the benefits it generates.

Second, what are the different ways a new technology enters the cost or expenditure function? The second question goes beyond the belief that new technologies increase (decrease) health care cost or expenditure because they are expensive (cheap). Along with new technologies, other factors may come into play. This fact essentially leads to the conclusion that any effort to control cost or spending associated with new technologies requires a good understanding of the ways a new technology affects cost. This chapter focuses on the second question with respect to the recent innovations in external beam radiation therapy to treat prostate cancer.

Usually technological change happens through gradual improvements and innovations on existing practices, techniques and treatments. The gradual and

subtle nature of technological change poses empirical challenges to define and measure accurately the overall technological change and its aggregate effect on cost and spending. In contrast, examining the effect of specific innovations is more feasible, precise, and therefore more attractive. Also, evidence from these specific innovations may be applicable in other comparable situations. In this light, the present study examines recent innovations in prostate cancer treatment—three dimensional conformal radiation therapy (3D-CRT) and intensity modulated radiation therapy (IMRT)—among Medicare patients in the United States.

This study seeks to answer the question how the health care expenditures behave over time after those innovations in external beam radiation therapy come into effect. The main goal of this research is to see the dynamics of the effect of the new therapy into cost or spending. It is plausible to assume that a new treatment may cause a onetime change in cost without affecting the rate of its growth. In other words it may only change the level of spending rather than its growth at the patient level. The alternative possibility is that new technologies also impact the growth of the unit cost of care. In accordance with the specific aim stated in Chapter 1, the hypothesis for this chapter is stated as follows.

Hypothesis: For individuals receiving 3D-CRT and IMRT:

H0.4.1: The ***growth*** of expenditure is not significantly different from the expenditure of those receiving standard treatment in the study period.

H1.4.1: The growth of expenditure is significantly different from the expenditure of those receiving standard treatment in the study period.

To explore this hypothesis, I estimate the historical trend of the patient level incremental cost of new treatments compared to the existing treatment. The long term trend of the incremental expenditure resulting from the use of a new treatment will help explain the dynamics of the relationship between treatment innovations and health care costs. The reminder of the chapter is organized as follows. Section 2 discusses recent literature about technological change in health care and its impact on cost and spending. In section 3, I discuss the analytical model of measuring the effect of the change in technology on expenditure. Section 4 includes the data and descriptive statistics. Finally, in sections 5 and 6, empirical results and their implications are discussed.

4.1.1 Innovations in external beam radiation therapy

Radiation therapy is one of the most common treatment options for various conditions including different cancers (NCI, 2009). Surgery and radiation are the two most commonly used treatments of prostate cancer. Radiation therapy is administered internally and externally. The former is also called Brachytherapy. Externally provided radiation is known as external beam radiation therapy (EBRT). Among the more recent innovations in radiation therapy, a three dimensional conformal radiation therapy (3D-CRT) was developed and used from late 1980s (Denmeade and Isaacs, 2002). A more advanced form of radiation treatment called intensity modulated radiation therapy (IMRT) came into use from the late 1990s. 3D-CRT has now become a commonly used practice (Speight and Roach, 2005, Mell et al., 2005).

3D-CRT involves a complex process of creating a three dimensional images of tumors from 3D digital data sets and delivering highly focused radiation to cancer cells while sparing normal adjacent tissue. (PAMF, 2009). Using conventional two-dimensional system, high dose and precise delivery is restricted as there is increased risk for acute and late toxicity (Kannan et al., 2005). There is additional amount of time and resources used in 3D-CRT over the conventional method particularly due to treatment planning. IMRT is an advanced form of 3D-CRT. IMRT has favorable outcomes compared to 3D-CRT in terms of rectal and bladder toxicity although both high dose treatments improve biochemical outcomes among all risk group of patients (Zelefsky et al., 2001).

Prior to these innovations in EBRT, a two dimensional standard radiation therapy (SRT) was used. Both new treatments are more costly than the treatments they replaced. In 1995, 3D-CRT needed 12% more technical and 38% more professional relative value units (RVUs) (Perez et al., 1997). IMRT requires more resources than 3D-CRT or conventional technique in terms of treatment planning and delivery time, computer hardware and software upgrades and physics quality assurance (Konski, et al., 2006).

4.2 Theoretical Construct

4.2.1 The treatment effect

I first discuss a general model[20] to evaluate the impact of a particular treatment, and then I discuss the empirical strategies used for this study. Let us

[20] Here I follow the standard model from the literature. For more see Heckman et al. (2006a, 2006b), Basu et al. (2007)

assume a treatment scenario with two alternative treatments, 0 and 1. Let Y_{0i} and Y_{1i} be the potential outcomes to individual i from treatment 0 and treatment 1 respectively. These outcomes are defined as

$$Y_{0i} = \mu_0(X_i) + \varepsilon_{0i}$$
$$Y_{1i} = \mu_1(X_i) + \varepsilon_{1i} \quad (1)$$

where $\mu_1(.)$ and $\mu_0(.)$ are the expected values of Y_1 and Y_0 respectively and X_i is a vector of observed covariates. ε_{0i} and ε_{1i} are unobserved random variables with an assumption that $\varepsilon_{0i} \neq \varepsilon_{1i}$. The effect of choosing treatment 1 versus treatment 0 is simply defined as $\Delta_i = Y_1 - Y_0$. In most treatment scenarios, treatment effects Y_{0i} and Y_{1i} are not observed for the same individual. If $T = 1$, we observe Y_1 and if $T = 0$, we observe Y_0. The outcome equation for observed Y conditional on treatment participation can be written in the form of a switching regression model[21] given as

$$Y = TY_1 + (1 - T)Y_0$$
$$= \mu_0 + (\mu_1 - \mu_0 + \varepsilon_1 - \varepsilon_0)T + \varepsilon_0$$
$$= \mu_0 + (\mu_1 - \mu_0)T + \{T(\varepsilon_1 - \varepsilon_0) + \varepsilon_0\} \quad (2)$$

The second and third lines of (3) result from the first line, equation (1) and a rearrangement of the terms. We can rewrite (2) as a standard regression model as

$$Y = \beta_0 + \beta_1 T + \varepsilon \quad (3)$$

However, (3) is not a standard regression model that we can estimate using the least square regression. There is a strong possibility that there exists a selection bias that individuals whose outcomes would have been different without treatment

[21] Also known as Quandt, Neyman-Fisher-Cox-Rubin-Roy model (Heckman and Vytlacil, 1999, Heckman, Urzua and Vytlacil 2006a, Basu et al. 2007, Imbens and Angrist, 1994).

could be the ones that select into the treatment. Note that I seek to find $\Delta_i = Y_1 - Y_0$. Equation (2) can be rewritten in the form of average causal effect of selecting a treatment known as average treatment effect of the treated (ATET) given by the formula (due to Angrist and Krueger, 2000) as

$$ATET = E[Y_{1i}|T=1] - E[Y_{0i}|T=0] = [E(Y_{1i} - Y_{0i})|T=1] + \{E(Y_{0i}|T=1) - E(Y_{0i}|T=0)\} \quad (4)$$

where the last is a bias term showing the additional effect on the treatment group had they not selected the treatment. Note that the bias term disappears if T_j is randomly assigned.

4.2.2 Estimation of Average Treatment Effect: Identification and Empirical strategy

I wish to estimate ATET given in equations (2)-(4). Let us define propensity score as $p(X_i) \equiv \Pr(T=1|X_i)$ which is the probability of individual i having been assigned to treatment 1. The propensity score is our identification tool. The identifying assumption in this case is that after conditioning on all of the observed characteristics that are known to affect treatment selection given by the propensity scores, both treatment and non-treatment groups are comparable, which can be put as,

$$E(Y_{0i}|p(X_i), T=1) = E(Y_{0i}|p(X_i), T=0) \quad (5)$$

Given this identifying assumption (equation (5)) the ATET is constructed as follows:

$$ATET = E(Y_{1i} - Y_{0i}|T=1) = \mathrm{E}\{E[(Y_{1i}|T=1,\ p(X_i)) - E(Y_{0i}|T=1,\ p(X_i))]T=1\} = \mathrm{E}\{E[(Y_{1i}|T=1,\ p(X_i)) - E(Y_{0i}|T=0,\ p(X_i))]T=1\} \quad (6)$$

$$= E\{\delta_x | T = 1\}$$

where, $\delta_x = E[Y_{1i}|X_i, T = 1] - E[Y_{0i}|X_i, T = 0]$e is a random variable that represents the set of differences in mean outcomes by treatment selection corresponding to each value taken by $p(X_i)$. In order to estimate (6) the method of matching on propensity score is used.

4.2.3 Reducing the bias and further identifying assumptions

Matching estimation is based on the assumption that selection is on observables. Given the estimation model using matching technique, we cannot rule out the presence of selection bias due to selection on unobservables. In this scenario, the identifying assumption given by (5) above is too strong. Heckman, Ichimura and Smith (1997) and Heckman, Ichimura and Todd (1998) extend the matching method to include a semi-parametric conditional *difference-in-differences* (d-i-d) matching estimator with a weaker identifying restriction. A d-i-d matching estimator removes the bias associated with fixed factors such as individuals' time-invariant characteristics. From equation (4) the bias is defined

$$B(X) = E(Y_0|X, T = 1) - E(Y_0|X, T = 0) \quad (7)$$

For d-i-d matching, the identifying assumption is:

$$E(Y_{0t} - Y_{0t'}|p(X_i), T = 1) = E(Y_{0t} - Y_{0t'}|p(X_i), T = 0) \quad (8)$$

where the subscript t' and t denote the pre-treatment and post-treatment outcomes. The empirical method to estimate ATET given by equations (4, 6) is the matching estimator given as:

$$ATET = \delta^M = \sum_{i\in\{T=1\}} \omega_{N_0,\,N_1}(i)[Q_{1,i} - \sum\nolimits_{j\in\{D=0\}} w(i,j)Q_{0,j}] \quad (9)$$

Here $\omega_{N_0,\,N_1}(i)$ is added as a weight that accounts for heteroskedasticity and scale. $Q_{1,i}$ and $Q_{0,j}$ are defined as $(Y_{1it} - Y_{1it'})$ and $(Y_{0jt} - Y_{0jt'})$ for treatment and comparison groups respectively. Matches for each participant are constructed by taking weighted average over comparison group members. Among the various weighing schemes, local linear matching is the most suitable for d-i-d estimator (Heckman et al. 1997). The local linear weight is given as:

$$w_{N_0,\,N_1}(i,j) = \frac{G_{ij}\sum_{k\in T_0} G_{ij}(X_k - X_i)^2 - [G_{ij}(X_j - X_i)[\sum_{k\in T_0} G_{ij}(X_k - X_i)]}{\sum_{j\in T_0} G_{ik}\sum_{k\in T_0} G_{ij}(X_k - X_i)^2{}_1 - (\sum_{k\in T_0} G_{ik}(X_k - X_i))^2} \quad (10)$$

where $G_{ik} = G\left(\frac{X_i - X_k}{a_{N_0}}\right)$ is a kernel function and a_{N_0} is a bandwidth parameter. Using local linear weight instead of other weights such as kernel weight causes conversion faster at boundary points and adapt better to different data densities.

4.3 The empirical work

4.3.1 Estimation strategy and data

This study uses the SEER Medicare-linked database which is created linking two large population based sources of data. The data from Surveillance, Epidemiology and End Results (SEER) program of cancer registries is linked to data from Center for Medicare and Medicaid Services (CMS) of persons' Medicare claims

for all covered services. The SEER part of data contains demographic, clinical and cause of death information for persons with cancer.

The Medicare part of data contains information associated with all eligible claims for corresponding cancer cases from SEER data. The Medicare part also contains information on date of service, diagnosis, procedures, provider type, claims and payments, and inpatient stays covered under the Part A and B of the Medicare program. Within the Medicare data, there are three sources of data—inpatient, outpatient and carrier claims. Medicare inpatient claims include all Part A short stay, long stay, and skilled nursing facility by calendar year. The outpatient data contain all Part B claims from institutional outpatient providers including hospital outpatient departments and other clinics and facilities. Carrier claims, also known as National Claim History (NCH) records, includes all Part B claims from physicians and other non-institutional providers. The SEER database currently covers 26 percent of the US population by its 16 registry sites across the United States.

4.3.2 Case selection and sub-samples

This study uses only prostate cancer cases from the SEER data. The population studied includes all Medicare patients in the SEER data who were diagnosed with and treated for non-metastatic prostate cancer from 1991 to 2002 and who received external beam radiation therapy (EBRT) as their definitive treatment.

Current Procedural Terminology (CPT) codes[22] were used to identify patients who received conventional standard radiation therapy (SRT), 3D-CRT and IMRT. To be eligible for inclusion, the patient is required to receive treatment planning for radiation therapy given by CPT codes 77260-77299. Receipt of three dimensional treatment planning (CPT code 77295) was used to identify 3D-CRT cases and EBRT treatment delivery codes G0174 and 77418 were used to identify IMRT cases. From these selected cases, patients who received Brachytherapy only were removed. Recipients of SRT were classified as the control group and the recipients of new treatments were regarded as the treatment group. The dataset was created by combining SRT with 3D-CRT and IMRT with dichotomous variables indicating treatment and control groups.

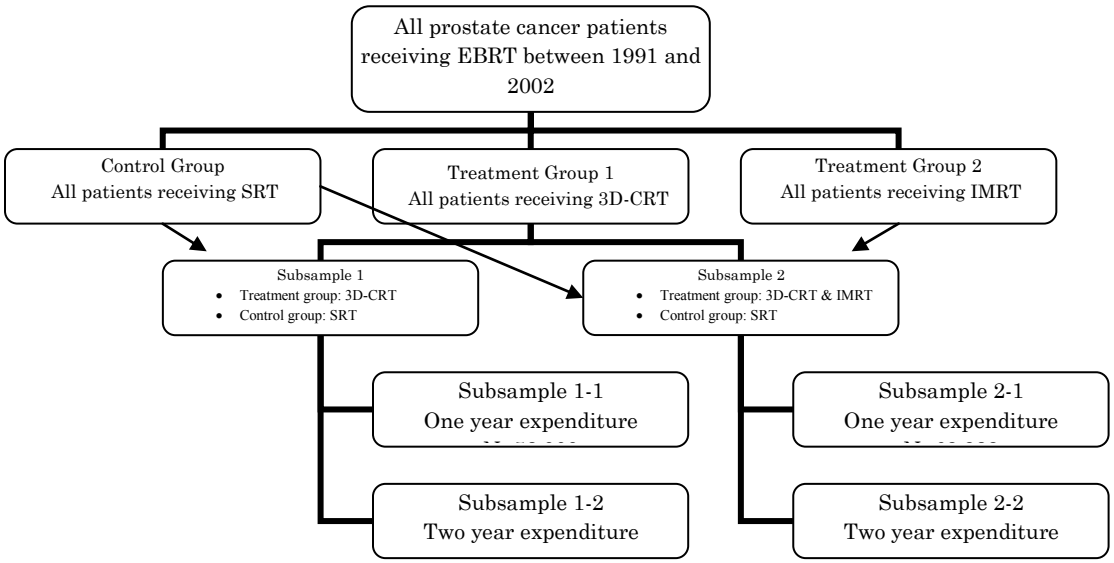


Figure 1: *Selection of subsamples*

[22] Comprehensive list of codes were obtained from Wong, et al. (2006).

Only those whose claim records were available for at least one year after and six months before the treatment date were included and those who are enrolled in HMOs were excluded. After these inclusion criteria, 64,157 cases were eligible for the study. Finally, sub-samples were created combining different treatment groups and further classifying subjects into those having one year of claims and those having two years of claims. Cases having less than one year (or two year) of claim history from the start of the treatment date were removed from one year (or two year) subsamples. The subsamples that include two year expenditure have fewer observations because not all selected cases had at least two year worth of records available. Figure 1 shows how subsamples were created with number of observations.

4.3.3 Key Variables and descriptive statistics

Treatment choice:

Figure 2 shows the trends for treatment choices for the whole study period among patients who received external radiation therapy. All diagnosed patients receiving SRT were treated as reference group. For the treatment group, there are two other groups: 3D-CRT and IMRT. In the first subsample, SRT cases are combined with 3D-CRT cases only. In the second subsample, both 3D-CRT and IMRT cases are included as treatment group.

Expenditure:

The key variable for this study is the difference between the pre treatment and treatment period all-cause health care expenditures for one and two year

periods. Expenditure in any period was calculated by aggregating all inpatient, outpatient and physician claims for that period. Nursing home, hospice or prescription drug claims were not included. The cutoff date for pre treatment and treatment period expenditure was the date 90 days before the date treatment planning was started. In case date of diagnosis was less than 90 days before treatment planning, then the date of diagnosis was used as the cut off date. One year expenditure for the treatment period was calculated for 365 days after the cutoff date and two year expenditures were calculated for 730 days after the cutoff date. If expenditures were not available for the full treatment periods, mainly due to patients' deaths, the patients were excluded. Pre treatment expenditures were calculated for the same length as treatment period expenditures. If records of claim were not available for the full one or two year pre treatment periods, then they were imputed for the remaining period using average daily expenditures. However, patients having less than 180 days of pre-treatment claims were removed.

Another adjustment was made in the treatment expenditure of people in the last year of their life. If anyone died within one year of treatment period, their treatment expenditure is distorted because of increased cost in the end of life care. I used the estimates from earlier studies (Lubitz, and Riley, 1993 and Hoover et al. 2002) to adjust the last year of life expenditures. Finally, the differenced expenditures were found by subtracting the pre-treatment expenditure from the treatment period expenditure. All expenditures are adjusted for current rate of inflation using the consumer price index and are expressed in 2005 dollars.

The study uses claims rather than reimbursements as a measure of expenditure for a number of reasons. First, it is assumed that the cost of new technologies, which essentially enters the cost as an input cost, is more directly reflected in the provider claims without any lag. On the other hand, Medicare reimbursements rates might be less sensitive to the true cost of new treatment than claims. Second, the information about the payment might be incomplete in the dataset because payments are made from different sources. Third, the main purpose of this study is to see the incremental cost of new treatments using differenced rather than absolute expenditure values. So, differencing and using control group will take care of much of the bias resulting from the use of claims.

4.3.4 Summary Statistics

Table 1 shows the summary statistics of the variables used in the empirical estimation for all 4 subsamples by treatment groups. All variables included in the table except treatment period expenditure and differenced expenditure are used to calculate the propensity score. The continuous age variable rather than categorical variables is used in the empirical model. In both samples, notably 3D-CRT group have higher pre-treatment expenditure, lower co-morbidity score and lower gap from diagnosis to treatment. Also, socio-economic differences also seem to have played role in treatment choice.

Figure 2 shows treatment choice over time for all treatment groups in subsample 2-1. Since samples 1-1, 1-2 and 2-2 are only the subset of 2-1, treatment choice over time for subsample 2-1 is more realistic. The proportion of people

receiving 3D-CRT grows continuously until 2001 after which it starts falling. The reason for the fall in 3D-CRT seems to be another new treatment IMRT which came into effect right around that time. So, those people who otherwise might get 3D-CRT may have received IMRT decreasing the proportion of 3D-CRT. The choice of IMRT sharply increases in 2001 and 2002. The proportion of patients receiving SRT continuously declines from near 100 percent in 1991 to 16 percent in 2002.

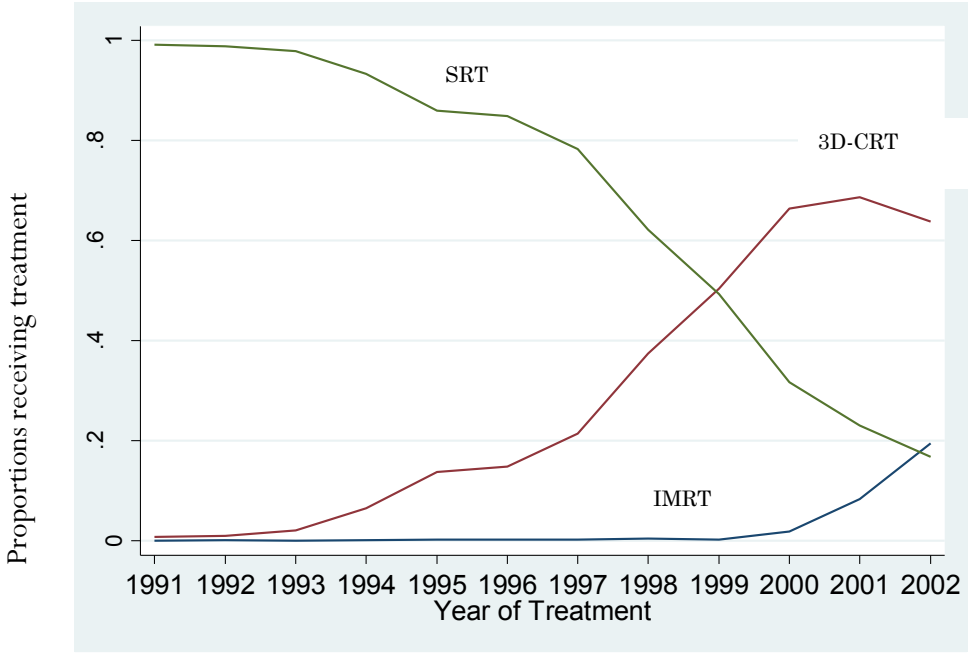


Figure 4.2: *Treatment choice over time*

Table 4.1: Summary Statistics for all subsamples

	3D-CRT only						**3D-CRT and IMRT**					
	One Year Expenditure (1-1)			Two Year Expenditure (1-2)			One Year Expenditure (2-1)			Two Year Expenditure (2-2)		
Variables	SRT N= 35355	3D-CRT N= 20978	Overall N= 56333	SRT N= 29503	3D-CRT N= 19925	Overall N= 49428	SRT N= 35355	3DCRT and IMRT N= 23359	Overall N= 58714	SRT N= 29503	3D-CRT and IMRT N= 22228	Overall N= 51731
Pre treatment expenditure ($)	13855	15351	14423	18248	24027	20620	13855	15992	14737	18248	24878	21196
Treatment period expenditure ($)	54181	75730	62359	67738	96945	79725	54181	78729	64310	67738	100253	82195
Differenced expenditure ($)	40788	60571	48296	48855	72602	58601	40787	62932	49925	48855	75046	60500
Charlson co-morbidity score	2.28	1.96	2.16	2.37	1.94	2.2	2.28	1.93	2.13	2.38	1.9	2.16
Mean length from diagnosis to treatment (days)	541	404	489	392	360	376	542	443	501	392	393	393
Married (%)	75	72	74	75	72	74	75	72	73	75	72	74
Mean age at diagnosis (years)	72.43	72.3	72.38	72.4	72.32	72.37	72.43	72.21	72.34	72.4	72.22	72.32
Age group (%)												
Below 65	7.47	7.47	7.47	6.17	6.95	6.79	7.47	8.02	7.7	6.17	7.57	6.79
65-69	22.26	21.98	22.15	22.41	22.13	22.34	22.26	22.11	22.2	22.41	22.25	22.34
70-74	34.54	34.73	34.61	36.42	35.16	35.73	34.54	34.48	34.51	36.42	34.88	35.73
75-79	25.99	27.08	26.41	26.85	27.32	26.9	25.99	26.72	26.29	26.85	26.96	26.9
80-84	7.78	7.56	7.7	6.86	7.39	7.05	7.78	7.48	7.66	6.86	7.28	7.05
85+	1.96	1.18	1.66	1.29	1.04	1.19	1.96	1.18	1.64	1.29	1.06	1.19
Races (%)												
White	84	82	83	85	82	84	84	82	83	85	82	84
Black	10	11	10	9	11	10	10	11	10	9	11	10
Other	6	7	6	7	7	6	6	7	7	6	7	7
Zip Code level variables (mean)												
Income	25542	26187	25787	25704	26270	25936	25543	26620	25986	25704	26740	26163
Percentage black	11.57	12.29	11.85	11.39	12.19	11.72	11.57	11.97	11.74	11.39	11.85	11.59
Percentage white	72.85	72.33	72.65	73.4	72.5	73.03	72.85	72.3	72.62	73.4	72.52	73.01
Percentage Hispanic	10.99	11.01	11	10.66	10.96	10.79	10.99	11.36	11.15	10.66	11.29	10.94
Percentage with college degree	28.35	28.35	28.35	28.56	28.45	28.51	28.35	28.94	28.59	28.56	29.08	28.79
Percentage with less than High school	16.95	17.72	17.24	16.71	17.63	17.1	16.95	17.6	17.22	16.71	17.48	17.05
Percentage of households who do not speak English well	5.11	5.41	5.22	4.94	5.38	5.12	5.11	5.63	5.32	4.94	5.59	5.23

4.3.5 Estimation of Propensity Scores

Calculating propensity score of treatment selection is the first step in the empirical analysis. In the literature[23], logit models are used in order to estimate the propensity scores $p(X_i)$. For the purpose of this study, I have made some additional assumptions in order to estimate the propensity scores. The estimation method is more suitable to the nature of the data.

Using simple logit estimation cannot accurately estimate the probability of selecting into treatment as the data are divided in clusters and cohorts. To this purpose, two unique characteristics of the data are given consideration.

First, the dataset used in the study is generated in 13 different SEER registries at different locations[24] of the US. Owing to historical and practice style differences the probability of selecting into a treatment may differ by locations. Second, the dataset constitutes a series of repeated cross sections as well as longitudinal elements. This makes it possible to define cohorts of people based on the time or year the treatment or outcome occurs. For the purpose of current analysis, it is most useful to define cohorts of people based on the year they started treatments. This is intuitive because the probability of selecting into treatment is correlated with years treatment started. Since we are considering the use of a new technology, it is highly appropriate to allow for the year effect while constructing the probability of selecting a treatment.

[23] Most notable are Dehejia and Wahba (1999 and 2002)

[24] There are 18 SEER locations in 2010. As of 2002, there were only 13 SEER locations.

In order to take account of the effect of those clusters and cohorts, a multilevel mixed model is used to estimate the propensity score. The propensity score function can be defined as

$$\Pr(T = 1|X_i) = f(X_i) + \varepsilon_i \quad (11)$$

where X_i includes all the factors affecting treatment choice. In estimating this equation using a standard model such as generalized linear model it is assumed that responses are independent given the covariates X. However, due to the existence of multiple cohorts and clusters in the data, there will often be unobserved heterogeneity at the cluster level caused by confounders that are either unobserved or unknown. For example the adoption of a new technology may be faster in some areas which makes some people more likely to chose a new treatment than others. So there is dependence among the units due to unobserved heterogeneity at the cluster level even for controlling observed heterogeneity.

In addition, the clusters are crossed with occasions, such as the use of a new treatment is crossed with the times when those treatments become available or when they become more widespread. We can model this dependence and the cross effects by splitting the error term into components for each level (Skrondal and Rabe-Hesketh, 2008) and we can rewrite our model (11) as:

$$Z_{ijt} = \vartheta_{ijt} + \xi_{1j} + \xi_{2t} + \epsilon_{ijt} \quad (12)$$

where $Z_{ijt} = Pr(T = 1|X_i)$, and $f(X_i) = \vartheta_{ijt}$. The error term is now broken into three parts where ξ_{1j} and ξ_{2t} are random intercepts for clusters and years respectively and ϵ_{ijt} is residual error term assuming:

$$\xi_{1j} \sim N(0, \psi_1), \qquad \xi_{2j} \sim N(0, \psi_2) \ \ and \ \ \epsilon_{ijt} \sim N(0, \theta).$$

This is known as two-way error-component model or crossed random effect model. To estimate (12) using crossed-random effects model, clusters are treated as level-2 units with random intercepts specified for them and years are treated as level-3 random intercepts. For level 3 dummy variables for years are constructed and the coefficient on dummy variables will be the random intercept imposing assumptions of (12). Then the estimating equation of (12) is written as

$$\Pr(T = 1|X_i) = \boldsymbol{X_{ij}}\beta + u_{jt}^{(2)} + \sum_p u_{jt}^{(3)} d_{pij} + \epsilon_{ijt} \qquad (13)$$

Equation (13) is estimated using maximum likelihood method.

Propensity Scores:

The propensity scores were calculated using the model specified above. The distribution of propensity score is shown by kernel density plots in Figure 3 for two subsamples. Figure 3a shows the distribution of propensity scores for subsample 1-1 and 3b shows that for subsample 2-1[25]. The graph also shows the overlap of the support where we can identify the treatment effect. Although there is a good deal of overlapping, we cannot identify the treatment effect over the entire (0, 1) support[26].

[25] The distribution of propensity scores for samples 1-2 and 2-2 are not shown but very similar to those that are shown.

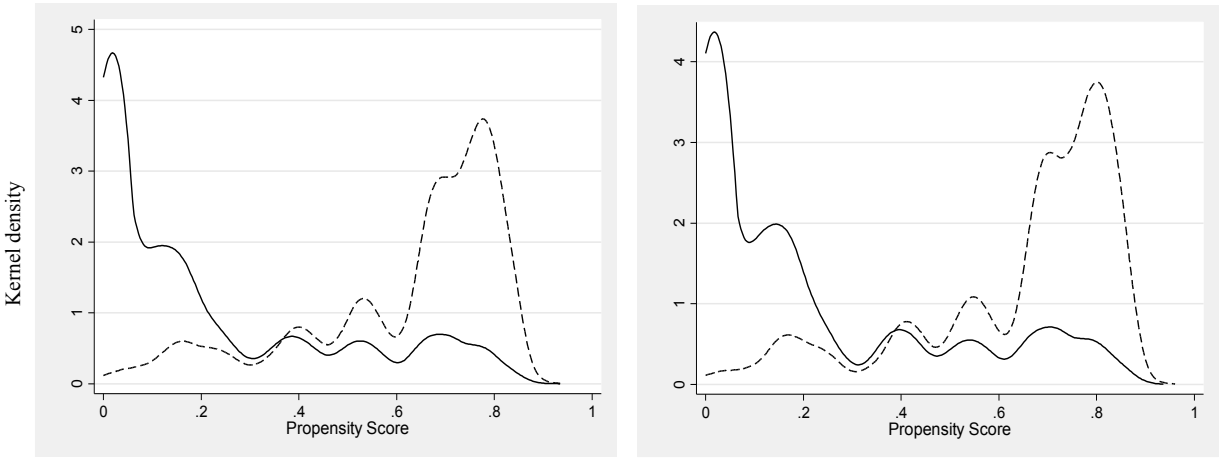
[26] Identification of treatment effect by propensity score matching requires that there are matching scores of treatment and control group. The distribution of propensity scores show that it is not evenly distributed in (0, 1) support. Propensity score for either group is not available towards the higher end of the support.

4.3.6 The issue of identification

The identifying assumption in propensity score model is that conditional on propensity score, the choice of treatment and outcome are independent. Once we control for all pre-treatment information, any change in post-treatment expenditure is purely random—patients incur expenditure increases due to other changes (such as new illnesses) irrespective of treatment status. However, the treatment assignment is not randomized and it is also possible that there are unobserved factors that affect the choice of treatment and spending. The major identification issue is how to minimize the potential bias arising from the possible endogeneity of treatment selection. In our model, endogeneity will be present if a particular group of patients who select into a particular treatment also have higher or lower expenditures than others. For example, if sicker or higher cost patients select more advanced technology then the effect of treatment cannot be identified or it will be overestimated. Similarly, same thing will happen if high cost providers are more likely to offer more advanced treatments.

There are some arguments to rule out the existence of endogeneity or rule out its significant impact if there is any. The first argument is that there is some sort of randomization in treatment assignment because people select a particular treatment versus another based on time, location and provider. This denies a possibility that sicker or high cost patients are systematically subjected to a specific treatment. The effect of year or location in treatment selection is observed and included in the propensity score model including many other pre-treatment

variables that might affect the treatment selection. The second and stronger argument is based on the use of pre treatment expenditure—the critical identifying technique used in this study. The use of pre-treatment expenditure will eliminate or minimize any patient or provider level fixed factor that subjects patients to treatment or no treatment based potential treatment expenditures.



(a) Distribution of propensity score for sub-sample 1-1

(b) Distribution of propensity score for sub-sample 2-1

Figure 4.3: Kernel density plots of propensity score distribution for two subsamples

4.4 The Results

Empirical estimation uses the strategy and identification technique explained above. In addition to the estimates made for the full sample, further estimates are made for all treatment cohorts created based on the year they started treatment. So estimates are made for each year for the study period 1991-2002. This allows us to see how spending changed over time after the adoption of a new technology.

4.4.1 The effect of 3D-CRT only

In order to see how the effect of a particular innovation on spending behaves in the long run, I first estimate the incremental effect of 3D-CRT excluding all IMRT cases. The estimated results using propensity score local linear matching using d-i-d extension are presented in Table 2. Overall, 3D-CRT has a highly significant effect on both one and two year spending. The differential spending for one and two year periods are $8,627 and $12,242 respectively. The cohort estimates show that the incremental effects are not statistically significant for the first 3 years of treatment 1991-1993. The treatment effects are both statistically and economically significant for the rest of the years.

Table 4.2. Summary of the results from empirical estimation for all subsamples and cohorts

	3D-CRT only				3D-CRT and IMRT combined			
	One Year spending		Two Year spending		One Year spending		Two Year spending	
Sub-samples/ Cohorts	Difference ($)	T-stat	Difference ($)	T-stat	Difference ($)	T-stat	Difference ($)	T-stat
1991	$479	0.07	-$4,562	-0.59	$430	0.06	-$5,066	-0.68
1992	$1,761	0.34	-$310	-0.04	-$1,261	-0.19	-$608	-0.08
1993	$914	0.35	-$1,026	-0.23	$1,999	0.78	-$1,606	-0.37
1994	$5,440	2.13	$13,600	3.18	$5,983	2.37	$12,379	2.96
1995	$11,376	5.67	$13,147	4.45	$11,185	5.59	$13,475	4.61
1996	$16,074	7.84	$14,422	5.06	$14,984	7.15	$14,298	5.04
1997	$13,336	8.44	$12,356	5.37	$12,512	7.97	$12,927	5.71
1998	$13,977	9.30	$14,993	6.50	$14,086	9.27	$14,974	6.51
1999	$10,195	6.68	$16,612	6.47	$10,829	7.02	$16,905	6.59
2000	$9,839	7.08	$14,760	5.86	$11,477	8.10	$15,507	6.20
2001	$8,316	4.34	$11,297	3.85	$11,636	5.82	$14,051	4.71
2002	$6,319	2.40	$12,641	3.99	$14,136	5.09	$18,003	5.73
Overall	$8,627	12.61	$12,242	12.06	$11,836	16.42	$14,724	14.14

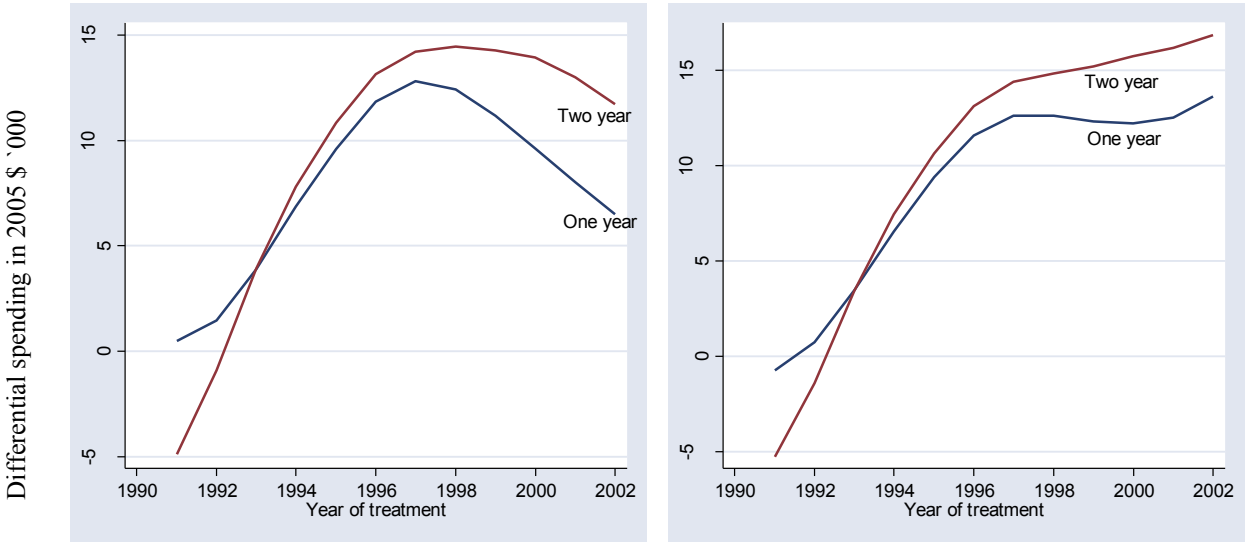
Notes: Spending is reported in 2005 constant dollar terms. S.E. are not reported to save space.

The trends of differential spending are also presented using the Lowess plots in order to smooth out the trends. Figure 4(a) shows the trends for 3D-CRT spending for one and two year treatment periods. The long run behavior of incremental spending is inverted U-shaped. The incremental spending of treatment starts out as low and insignificant for both treatment periods. After a few years, the differential spending of 3D-CRT over standard therapy starts increasing and becomes substantially higher. Both one and two year differential spending grow similarly except that two year spending remains higher for longer time. Towards the end of the study period, the differential spending shows a decreasing tendency for both subsamples. The initial growth in spending eventually takes a reverse trend.

4.4.2 Adding IMRT

In order to see how the behavior of spending changes when there is another innovation, I added IMRT cases in the treatment group and did a parallel estimation as 3D-CRT. In this strategy, the treatment group includes 3D-CRT and IMRT cases and control group includes SRT cases. On the one hand, the rationale of adding IMRT cases is that like 3D-CRT, IMRT is a new innovation and more advanced treatment in radiation therapy and it substitutes 3D-CRT. Patients are given either one of the technologically advanced new treatments or conventional therapy. On the other hand, trend analysis of IMRT alone like 3D-CRT is not feasible because of the short span of time that IMRT had been used in the dataset.

Although small numbers of cases are available for earlier years, a substantial number of cases are available only from the year 2000.



(a) 3D-CRT only (b) 3D-CRT and IMRT

Figure 4.4. *Lowess plots for the trends of estimated incremental expenditure of the treatment selection for the study period.*

Estimates are made using the same technique as for 3D-CRT and estimated results are presented in Table 2. For the whole sample, new therapies account for $11,836 and $14,424 spending for one and two years respectively. As in 3D-CRT, cohort estimates show that the incremental effects were not statistically significant for the first 3 years of treatment 1991-1993 and both statistically and economically significant thereafter. The trends of spending are markedly different towards the end of the study period, however. The trends are also shown using the Lowess plots in Figure 4 (b). With IMRT added, the trends of differential spending for both one and two year look very similar with those of 3D-CRT during the first half of the study period. However, during the second half the behaviors of incremental

spending become completely different—they mimic the behavior of IMRT as a treatment choice (Figure 2). After the introduction of IMRT, the incremental spending for new treatments start rising once again.

4.5 Sensitivity Analysis and Robustness Checks

The key assumption for identifying the treatment effect is that the choice of treatment is independent of any observed factors that also affect the expenditure. This study uses the richness of the data and suitable techniques to make sure there is no bias associated with unobserved patient characteristics. In order to see how robust these estimates are against any misspecification, I do a sensitivity analysis and robustness checks in this section.

The basic identification assumption in the propensity score matching analysis is that the factors affecting the choice of treatment are observable and there is no confounding between the choice of treatment and outcome. The estimation of treatment effect will be biased if there is a confounding between the choice of treatment and the outcomes. In the context of present study, the treatment effect will be overestimated if the patients who choose more advanced forms of treatment are those who tend to consume more or better health care and thereby have higher health care spending. Although there is no direct method of measuring confounding effects, we can still employ some of the measures to check the robustness and sensitivity against specification errors.

4.5.1 *Sensitivity analysis*

I use the bounding approach (Rosenbaum, 2002; Becker and Caliendo, 2007) proposed by Rosenbaum (2002) in order to check the sensitivity of estimated treatment effects to any hidden bias. This analysis checks the robustness of estimated treatment effects with respect to assumptions about an unobserved covariate that is associated with both treatment and response. Although, bounding approach is not the test for the existence of the confounding effects, it provides the way to determine how strongly an unmeasured variable must influence the selection process to undermine the matching estimates. Let $U \in \{0,1\}$ be such a confounder and Y be the outcome variable which is a continuous variable in our case. In a situation when two individuals with similar observed characteristics may have different chances of receiving a treatment and bounds on the odds ratio that either of the individual will receive treatment is constructed as:

$$\frac{1}{\Gamma} \leq \frac{P_i(1-P_j)}{P_j(1-P_i)} \leq \Gamma$$

where P_i, P_j are the probabilities of receiving treatment by individuals i and $j, i \neq j$. The statistic Γ is defined such that $\Gamma = 1$ if both individuals have the same probability of receiving the treatment. For $\Gamma > 1$, meaning that there are different odds of receiving treatment due to unobserved covariates, the distribution of treatment assignments is unknown but bounded with a range of significance levels. In order to construct such bounds Mantel and Haenszel (MH) test statistic for observed outcome is used. The lower bound suggests the case when treatment effect

is underestimated while upper bound is in the case when treatment effect is overestimated.

The bounding approach is applicable when the outcome is binary. Since the outcome variable in this analysis is expenditure, which is continuous, a binary outcome variable is created for this purpose. The most likely source of confounding was the unobserved patient or provider characteristics that may lead high cost patient select into advanced treatments overestimating the treatment effect. Mean value of the differenced expenditure was chosen to dichotomize the outcomes into high and low expenditures. The odds of selecting into treatment are defined as:

$$P_{ij} \equiv \Pr\left(T = 1 | X = x, I(Y > y^*) = j\right), \qquad i, j \in \{0, 1\}$$

which is the probability that $T = 1$ in each of the four groups defined by observed covariates X and the binary transformation of outcomes.

Table 3 shows the results of the sensitivity analysis. For each sample, overall samples and treatment cohorts, I calculated the upper bounds for which the MH test statistic is still significant at 1% significance level. This test did not apply to cohorts for whom treatment effects were not significant. In the first column, for example, the Rosenbaum bound for the overestimation of treatment effect Γ^+ is 1.4. This means that the calculated treatment effect is sensitive to bias that would increase the odds of receiving treatment beyond 1.4. However, it will remain insensitive if odds are up to 1.4. The highest upper bounds for insensitive regions for various samples and cohorts range from 1.2 to 3. The upper bounds for estimated treatment effects are smaller for treatment cohorts than for overall

samples indicating the smaller probability of selection bias. Further, the bounds get larger until the middle of the study period and then they continuously decline for the remaining years. Note that having an upper bound greater than 1 does not necessarily mean that there is a positive selection bias. The lower bounds for bias for estimated treatment effects is not interesting given the assumption of overestimation of treatment effect.

Table 4.3: Estimation of Rosenbaum bounds to check the sensitivity of results

Cohorts/ Sub-samples	3D-CRT One Year Γ^+	3D-CRT Two Year Γ^+	3D-CRT and IMRT One Year Γ^+	3D-CRT and IMRT Two Year Γ^+
1991	‡	‡	‡	‡
1992	‡	‡	‡	‡
1993	‡	‡	‡	‡
1994	1.4	1.4	1.2	1.2
1995	2	1.8	1.8	1.8
1996	2.8	2	2.8	2
1997	2.6	1.8	2.6	1.8
1998	2.4	2	2.4	2.2
1999	1.8	1.6	1.8	1.8
2000	1.6	1.4	1.6	1.4
2001	1.4	1.2	1.4	1.4
2002	1.2	1.2	1.6	1.4

Notes:
Γ^+ is the upper bound of the odds of receiving the treatment
‡ denotes results are irrelevant due to the insignificance of the estimates

4.5.2 *Robustness Checks*

I also use a parametric approach to estimate the treatment effect using a multivariate regression model. In order to control potential bias associated with

treatment selection differenced expenditure rather than absolute expenditure was used as the dependent variable. Again, differencing was our main strategy to reduce the bias associated with patient level fixed effect. Further, I created an indicator variable of treatment for each cohort that will capture the treatment effect for that cohort. Other independent variables included a host of control variables including a full set of year dummies. Generalized Linear Model (GLM) with Log link and Gamma distribution was used to estimate the regression model[27].

Estimates from the regression model are presented in Table 4. The estimates from parametric and non parametric methods broadly agree although there are differences in magnitudes and fluctuations. Note that these two methods are not meant to be equivalent in terms of specifications. One year spending for 3D-CRT is very close in terms of both magnitude and trend in both methods. The differences in two year spending for 3D-CRT are, however, more pronounced at times. For both 3D-CRT and IMRT combined, the estimates from parametric methods show a sudden upward jump and stay or slightly fall before they start rising again unlike non parametric estimates when they rise more gradually, remain relatively flat for sometimes and tend to rise again.

4.6 Discussion and conclusion

This study aimed at analyzing the behavior of health care spending related to innovations in radiation therapy over a long period of time. Two innovations in radiation therapy were selected for study—3D-CRT and IMRT. Evidence from 3D-

[27] Among various parametric models, GLM model with log link is more suitable for this type of data. See Manning, Basu and Mullahy (2005) for complete treatment to the approach.

CRT suggests that incremental spending tends to rise after a few years of adoption. During the early stage of adoption, the incremental effects were not substantial. Spending owing to new treatment not only increased later on, it grew fairly consistently for a certain period of time before it started subsiding towards the end of 12 year study period 1991-2002. It is interesting and particularly important to note that although it is a cost increasing technology (Perez et al., 1995), the cost does not seem to be different or to increase all of the time.

Table 4.4: Parametric estimation of the treatment effects for subsamples and treatment cohorts

Cohorts/ Sub-samples	3D-CRT One Year ($)	3D-CRT Two Year ($)	3D-CRT and IMRT One Year ($)	3D-CRT and IMRT Two Year ($)
1991	-2,738†	-3,794†	-10,556†	-12,029†
1992	-1,830†	-2,015†	2,718†	1,235†
1993	2,520†	1,824†	-2,066†	-3,328†
1994	7,105‡	6,890*	15,096‡	15,299*
1995	11,910*	11,819*	12,669*	12,511*
1996	15,418*	15,160*	11,829*	12,025*
1997	12,512*	12,919*	12,337*	12,807*
1998	12,491*	12,586*	10,259*	10,374*
1999	7,917*	8,048*	9,656*	9,786*
2000	8,970*	9,472*	10,560*	11,120*
2001	6,143*	7,744*	5,568*	7,187*
2002	5,467*	8,631*	8,264*	12,048*
Overall	8,341*	10,099*	9, 052*	10,849*

† Not significant at 5% level ‡ Significant at 5% level * Significant at 1% level

Another innovation was introduced in radiation therapy towards the end of study period. Estimates that include both 3D-CRT and IMRT as new treatment

versus the conventional treatment show that incremental spending does not subside but keeps increasing after IMRT was introduced. However, it is also noted that there was a brief slowdown of the spending growth during the very early stage of IMRT adoption. Towards the end of the study period, both one and two year incremental spending trends go upwards. The spending growth resulting from 3D-CRT was maintained from the introduction of IMRT.

The behavior of spending over time supports different hypotheses about how new technologies enter the health care cost and expenditure functions. During the initial adoption period, cost of 3D-CRT is not substantially different from the cost of conventional therapy. This suggests that cost plays an important role on acceptability of a new technology that may not substantially improve outcomes. This is also supported by studies (such as Perez et al., 1997) during the early stage of adoption that the overall cost of CRT was not different from that of SRT.

But as acceptance rate grows later in the period, the incremental spending grows as well. Perhaps it is the market power of care providers, rather than the actual cost of production, that caused the cost of treatment to go up as acceptability increased. This further implies, as suggested by previous studies (Keeler et al., 1999), that hospitals that adopt new technology before most others may be able to charge more due to their competitive edge in the market causing the average expenditure to go up.

The eventual decrease in the incremental cost may come from two reasons, installation cost and competition. Health care providers who install new technology

based treatment facility may charge more than the normal amount in order to recover their installation cost during the initial period (Lotan et al., 2005). This may eventually come down after a reasonable period of time. On the other hand, competition among providers may also lead to reduced incremental spending as almost all service providers adopt the technology, no providers can charge the early adoption premiums for the new technology.

The rising and falling expenditure trend can result from the possibility that high cost providers are among the early adopters of new technology. As new technology becomes available only few hospitals are very likely to adopt them first driving the average expenditures upwards compared to the standard treatment. When almost all providers, including low cost providers adopt the technology, the average expenditure is very likely to go down.

The increasing trend of expenditure is reinforced with the introduction of IMRT—it seems to repeat the trend of 3D-CRT. This suggests that the adoption of new technology by hospitals is motivated by their goal of becoming the leader in providing the quality care (Teplensky et al., 1997) while maintaining or increasing the flow of revenues and/or profits. The conclusion is that the costs associated with innovations in health care do not only change the intercept, they also change the slope of the expenditure growth in the long run. This study finds that the nature of the growth of spending associated with a single innovation rises first before it starts declining. If there are a series of innovations, the upward trend of spending is likely to continue as we see the effect of IMRT on the behavior of spending. For additional

research, the findings of this study suggest that the role of new technologies to drive up cost and spending at least partly depends on the technology adoption behavior of the health care providers, such as who adopts the new technology first. The way health care market is organized and the speed by which a new treatment is expanded are essentially linked with that.

The scope of the analysis is limited to the behavior of cost of a treatment over time without accounting for its effectiveness. Further studies may focus cost-effectiveness analysis using these findings to draw policy relevant conclusions.

CHAPTER 5

SUMMARY OF STUDY, FINDINGS AND CONCLUSION

For the last couple of decades the US health care spending has been growing very rapidly, which is a major source of concern and policy debate at the national level. From early 1990's the health care spending increased by an average of approximately 7 percent (Schoen et al., 2009; Zuckerman and McFeeters, 2006) per year. This means that total health care spending is doubling every decade unlike the GDP which is growing at a much slower rate. The consequences of rising health care cost and spending are many and significant. One of them is the price rationing of health care. An increasing segment of US population is without health care coverage because it is unaffordable to them.

Health care reform has received the top priority in national policy reform. The goal of such reform is to provide affordable but high quality care to all individuals. This implies that controlling the growth of health care cost is one key objective of such policy.

It is widely agreed that technological change in health care is the major driver of health care cost and spending. However, there is no agreement in what share of contribution is made by technological change. The main purpose of this study is to understand the extent of the impact of technological change in health care.

There are two aspects of technological change that are important to know in order to understand the role of technological change. The first is what is the extent

to which innovations in medicine drive up health care cost and spending? The second aspect of technological advancement is the way it affects spending. The relationship between new technologies and their associated costs could be influenced by several factors in a complicated fashion. How these new technologies are produced, financed and marketed may determine the exact impact of their cost. Understanding the extent and mechanism by which a new technology actually translates into higher cost are main objectives of this study.

5.1 Study design and organization of the report

This study uses a retrospective research design with observational historical data. In order to ensure precision, this study uses only specific group of patients with a specific condition. The subjects are Medicare enrolled individuals aged 65 or above who were diagnosed with prostate cancer from 1991 to 2002. Specifically, this study seeks to measure the association between technological changes and health care spending attributable to prostate cancer treatment, management or care. The effect of technological change is found as a relative, not absolute, effect of medical advances specific to prostate cancer care.

The main report of the study is organized in three key chapters. Chapter 2 presents the long run growth picture of spending. One year spending associated with prostate cancer care was calculated. The calculated spending shows how short term (one year) cancer care cost following the diagnosis of cancer changed over time. The calculated costs are in addition to average increase in the health care spending

of the general population. It is assumed that the calculated costs of cancer care reflect all specific changes related to prostate cancer, i.e. technological change.

Chapter 3 uses outcome as a single measure of technological change. Prostate cancer caused death rate is used as the key outcome in this regard. Two assumptions are made in order to use particular study designs. The first assumption is that change in cost is 'caused' by changes in cancer care resulting from technological change. The second assumption is that in health care spending and cancer care technologies are endogenous to each other and therefore they are simultaneously determined.

Unlike Chapter 2, this chapter includes the calculation of the increase in health care spending with a denominator. So the chapter is a first step towards the cost-benefit or cost-effectiveness analysis of the technological change in prostate cancer care. However, cost-effectiveness or cost-benefit analysis is not the purpose of this study.

The last key chapter is Chapter 4, which is about measuring cost of specific technologies. The chapter has two objectives. First, it aims to measure how much the cancer care expenditure changed owing to these specific technologies. Second, how did the expenditure associated with new technologies behave over time? In other words, the specific interest was in the *intercept* and *slope* of the cancer care cost attributable to the specific cutting edge technologies in cancer care. The technologies included are three dimensional conformal radiation therapy (3D-CRT) and intensity modulated radiation therapy (IMRT).

5.2 Major findings and conclusions

All estimated costs are in 2005 dollars and costs, measured by expenditure or spending are all related to prostate cancer care, management or treatment. The average first year incremental spending following an individual's diagnosis of prostate cancer was $31,000 in 1993[28]. It increased to $66,000 in 2002. The total net increase in expenditure in 10 years' period more than doubled (i.e. 113% increase). The trend of expenditure for the diagnosed population was increasing throughout the period.

The increase in expenditure associated with the diagnosis and treatment was from $48,018 to $85,267 during the same period. The increases in treatment related expenses were more than that of diagnosis related expenses in absolute amounts. But the growth rate of treatment related expenses during 10 years' time was lower, i.e. 80 percent, compared to 113 percent for diagnosis related expenses.

Growth of expenditures by treatment type was also estimated for three treatment groups: radical prostatectomy, radiation therapy and watchful waiting. Different trends of treatment expenses were observed for these three groups. For those who receive neither surgery nor radiation treatment, expenditures grew slightly in the beginning and after a period of stability, started growing again. For the radiation group, the expenses actually decreased during the first half of the study period before they started rising again. The growth of expenses for the surgery group is totally different. Treatment related expenditure for this group

[28] The effect was not significant for 1992 and estimate is not available for 1991 due to the design of variable calculation. Data are available from 1991 and since the study design includes pre-diagnosis expenditure cases diagnosed in 1991 simply dropped out as they had no pre-diagnosis information.

grew throughout the study period. This suggests substantial and rapid changes in treatment choices for those who receive surgery as their definitive treatment option.

The findings from Chapter 2 suggest a substantial increase in health care expenditure that is explained by the changes in prostate cancer care during the study period. If all changes are loosely defined as technological changes, then technological change in the first year of prostate cancer care alone contributed about 100 percent increase in expenditure in 10 years' period. There were more substantial changes in treatment options than in overall care. Among treatment options, surgery saw the highest and the fastest growth of spending.

The next strategy was to estimate the growth of spending using an objective measure of technological change. In this case, technological change was measured by annual death rate caused by PCa as a proxy. So, the denominator of spending was a unit decline in death rate associated with prostate cancer. Estimates using single equation model range from $174 to $201, while using simultaneous model, the estimates range from $179 to $206 for a unit decline in the PCa caused death rates. These are the average amounts that cost per patient in a year following diagnosis if cancer related deaths were to decline by 1 per 100,000 elderly populations. Using a moderate estimate, it would add to $19,055 per patient in the population studied for the entire decline in death rate caused by prostate cancer. In other words, from 1993 to 2002, there was $19,055 increase in average expenditure which can be attributed to decline in PCa caused death rate from 277 to 173 per 100,000 individuals.

Interest also lies in what the cost is for one PCa death avoided. Using the same estimate as above, avoiding one prostate cancer related death in the 65 and older age group would cost $185,000 in the first year of care only.

Finally, estimates of cost and its growth were made for two important innovations in radiation therapy to treat prostate cancer. Estimates show that one year average cost were $8,627 and $11,836 higher than SRT for 3D-CRT and 3D-CRT and IMRT combined respectively. Similarly, two year cost differentials were $12,242 and $14,724 higher for 3D-CRT and 3D-CRT and IMRT combined respectively.

Year by year estimates for the two technologies were also calculated in order to examine the growth trends. Estimates for 3D-CRT showed that expenditures for the treatment grew before it started falling showing an inverted U-shaped trend for both one year and two year expenses. However, if IMRT treatment group were also included, the expenditure associated with the choice of new treatments as opposed to conventional radiation treatment kept growing throughout the study period.

The conclusion from this chapter is that new innovations in radiation therapy not only increased the cost of treatment, they also caused the rate of increase to grow. This suggests that the health care market structure is such that new technologies serve somehow as the instruments to enhance the market power of the health care providers.

The behavior of spending over time supports different hypotheses about how new technologies enter the health care cost and expenditure functions. This

suggests that cost plays an important role on acceptability of a new technology that does not substantially improve outcomes. As acceptance rate grows later in the period, the incremental spending grows as well. The role of new technologies to drive up cost and spending, therefore, at least partly depends on the technology adoption behavior of the health care providers, such as who adopts the new technology first.

This study is an attempt to measure the effect of technological change in health care spending and cost in the United States. This is an important area of research, but still there is a lack of studies focusing on the issue. Within its own limitations this study makes important contributions to this field of knowledge.

The conclusions from this study are drawn only from the information of a specific segment of the general population. Prostate cancer is, however, a major condition affecting elderly males and it has been given a high focus in care and management. The methods used are expected to apply to any similar conditions including all types of cancer.

In this research, disease specific health care costs are calculated as the marginal price of better care resulting from technological change. This type of research design and technique can be extended to other disease conditions to study the relative increase in health care resources devoted to provide care for those conditions.

A significant increase in health care expenditure in prostate cancer care may or may not be worth it for the gain made in outcomes. These findings may be used

to analyze the cost and benefits of technological change, which is not within the scope of this study.

Findings from technology specific study show that new technology may cause the cost not only to go up but also to increase over time. This suggests that new technologies are not only costly, they may cause the cost to grow even further because of the way new technologies are adopted and utilized.

The major limitation of this study is the study population. The findings are not applicable to the general population. Another limitation is it does not include prescription drug expenses, which make a significant component of total health care expenditure.

5.3 Direction for future research

The issues encountered and conclusions made in this study give rise to further research in this area. The important is finding an objective measure or an index of the use of health care technology. A way to measure the amount of technology used in care will provide a reliable and absolute estimate of the effect of technological change in health care spending.

Findings from this study can be used to measure the cost benefit or cost effectiveness of technological change in prostate cancer care. The estimated cost increases may be expressed in terms of a more common denominator such as quality adjusted life years (QUALYs). There may be better proxy measures of technological

change other than death rate. Using those measures will provide an interesting comparison to the findings from this study.

Since technology is an important contributor to overall health care spending and cost, the geographic variation in the use of latest innovations may also be exploited in order to estimate the effect of technology. The research question in this regard can be: If technology is a driver of spending, then to what extent does geographic variation in technology adoption explain geographic variation in spending?

Study of health care technology markets will be a very good extension to this study. The findings from this research suggest that technology adoption behavior of hospitals and speed of technology diffusion may have important implications for the increase in cost due to new technologies. The way health care market is organized and the speed by which a new treatment is expanded are essentially linked with that. Further research in this perspective will be crucial and have important policy implications.

APPENDIX A

Table A1. Full equation estimates of cancer related spending by year of diagnosis (Table 2.2 Estimates by diagnosis status)

Right Hand Side Variables	Coef.	Std. Err.	P>z	Expontiated Linear Prediction
Year*Diagnosis = 1				
1992	0.740	1.015	0.466	$12,301
1993	1.343	0.041	0.000	$31,137
1994	1.398	0.034	0.000	$33,179
1995	1.415	0.035	0.000	$33,995
1996	1.504	0.036	0.000	$38,161
1997	1.578	0.035	0.000	$41,862
1998	1.676	0.037	0.000	$47,282
1999	1.762	0.035	0.000	$52,228
2000	1.755	0.026	0.000	$50,209
2001	1.880	0.025	0.000	$57,945
2002	2.002	0.025	0.000	$66,434
Age	0.001	0.001	0.391	$9
Charlson Comorbidity Score	0.189	0.003	0.000	$2,115
Race—*Black*	-0.089	0.019	0.000	-$963
Race—*Other*	-0.174	0.022	0.000	-$1,815
Tumor Characteristics				
Multi-site	-0.056	0.118	0.634	-$628
Metastatic	0.057	0.026	0.032	$652
Unstaged	-0.040	0.021	0.060	-$441
Metro resident	-0.024	0.016	0.138	-$268
Therapy started	0.105	0.013	0.000	$1,145
% with College degree by Zip Code	0.001	0.001	0.210	$7
Mean income by Zip Code	0.000	0.000	0.044	$0
SEER Locations (Connecticut=0)				
Detroit	0.116	0.024	0.000	$1,359
Hawaii	-0.007	0.043	0.874	-$76
Iowa	-0.344	0.024	0.000	-$3,391
New Mexico	-0.226	0.034	0.000	-$2,288
Seattle	-0.254	0.026	0.000	-$2,564
Utah	-0.287	0.030	0.000	-$2,833
Atlanta Metro	-0.047	0.033	0.163	-$512
Rural Georgia	-0.121	0.085	0.155	-$1,284
Kentucky	0.086	0.032	0.007	$1,001
Louisiana	0.246	0.033	0.000	$3,111
New Jersey	0.483	0.026	0.000	$6,676
California	0.374	0.021	0.000	$4,608
Constant	8.359	0.141	0.000	

Table A2. Full equation estimates of cancer related spending by year of diagnosis (Table 2.2 Estimates by diagnosis and treatment status)

Right Hand Side Variables	Coef.	Std. Err.	P>z	Expontiated Linear Prediction in $
Year*Diagnosis = 1				
1992	0.54	1.184	0.46	8,960
1993	1.59	0.049	32.67	48,018
1994	1.66	0.040	41.16	51,658
1995	1.64	0.041	39.65	51,040
1996	1.71	0.042	40.25	55,188
1997	1.77	0.041	42.67	59,018
1998	1.85	0.043	43.21	65,625
1999	1.93	0.041	47.37	71,184
2000	1.90	0.030	64.01	67,027
2001	2.00	0.030	67.40	74,770
2002	2.12	0.030	71.60	85,267
Age	0.00	0.001	2.95	40
Charlson Comorbidity Score	0.20	0.003	69.69	2471
Race—*Black*	-0.09	0.021	-4.24	-1056
Race—*Other*	-0.19	0.024	-7.71	-2184
Tumor Characteristics				
Multi-site	-0.05	0.122	-0.43	-654
Metastatic	0.05	0.031	1.78	700
Unstaged	-0.02	0.025	-0.94	-295
Metro resident	-0.01	0.017	-0.71	-154
Therapy started	0.02	0.016	1.07	213
% with College degree by Zip Code	0.00	0.001	1.11	8
Mean income by Zip Code	0.00	0.000	-1.64	0
SEER Locations (Connecticut=0)				
Detroit	0.11	0.026	4.44	1494
Hawaii	0.01	0.046	0.13	74
Iowa	-0.31	0.026	-12.06	-3503
New Mexico	-0.20	0.037	-5.51	-2321
Seattle	-0.24	0.027	-8.88	-2768
Utah	-0.26	0.032	-8.02	-2911
Atlanta Metro	-0.05	0.036	-1.47	-644
Rural Georgia	-0.10	0.095	-1.01	-1147
Kentucky	0.03	0.034	1.02	446
Louisiana	0.20	0.037	5.54	2798
New Jersey	0.39	0.028	14.20	5823
California	0.37	0.023	16.45	5121
Constant	8.38	0.149	56.41	

APPENDIX B

Table B1. Full equation results from the single equation model
(Table 3.2 First year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome--Year 1	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B2. Full equation results from the single equation model (Table 3.2 Second year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome--Year 2	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B3. Full equation results from the single equation model (Table 3.2 Third year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome--Year 3	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B4. Full equation results from the single equation model (Table 3.2 Fourth year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome--Year 4	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B5. Full equation results from the single equation model (Table 3.2 Fifth year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome--Year 5	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B6. Full equation results from the single equation model
(Table 3.2 Average of first to fifth year outcome as the variable of interest)

Variables	Coef.	Std. Err.	z	P>z	[95% Confidence Interval]	
Outcome—Average of Year 1-5	-0.006	0.000	-38.200	0.000	-0.006	-0.006
Therapy started	0.713	0.012	61.080	0.000	0.690	0.735
Age	-0.017	0.001	-20.190	0.000	-0.018	-0.015
Charlson Score	0.044	0.002	19.940	0.000	0.040	0.049
Race-Black	-0.008	0.016	-0.520	0.602	-0.040	0.023
Race--Other	-0.015	0.019	-0.800	0.425	-0.053	0.022
Multisite PCa presentation	0.285	0.142	2.010	0.044	0.007	0.563
Metastatic PCa presentation	0.029	0.023	1.270	0.203	-0.016	0.074
Unstaged PCa presentation	-0.039	0.018	-2.220	0.026	-0.074	-0.005
Metro resident	0.104	0.014	7.370	0.000	0.076	0.132
% with college degree by Zip Code	0.001	0.000	1.460	0.144	0.000	0.001
Mean income by Zip Code	0.000	0.000	-1.640	0.100	0.000	0.000
Detroit	0.059	0.021	2.860	0.004	0.019	0.099
Hawaii	0.012	0.036	0.330	0.742	-0.059	0.082
Iowa	-0.415	0.020	-20.500	0.000	-0.454	-0.375
New Mexico	-0.229	0.028	-8.150	0.000	-0.284	-0.174
Seattle	-0.445	0.022	-20.520	0.000	-0.487	-0.402
Utah	-0.552	0.025	-22.030	0.000	-0.601	-0.502
Atlanta Metro	-0.167	0.028	-5.950	0.000	-0.222	-0.112
Rural Georgia	-0.133	0.076	-1.750	0.080	-0.281	0.016
Kentucky	-0.222	0.029	-7.610	0.000	-0.280	-0.165
Louisiana	-0.256	0.031	-8.390	0.000	-0.316	-0.196
New Jersey	0.166	0.024	7.020	0.000	0.120	0.213
California	0.012	0.018	0.640	0.522	-0.024	0.047
Constant	12.259	0.162	75.550	0.000	11.941	12.577

Table B7. Full equation results from the simultaneous equation model (Table 3.3 Average of first year outcome as the variable of interest)

	Equation 1 Dependent variable=Expenditure			**Equation 2** Dependent variable=Outcome year 1		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Outcome—Year 1	-206	5.37	0.000			
Therapy started	19959	391.71	0.000			
Age	-483	27.36	0.000	0.000	0.000	0.014
Charlson Score	1537	75.60	0.000	0.000	0.000	0.605
Race-Black	416	543.67	0.445	0.000	0.001	0.571
Race--Other	103	650.87	0.874	-0.002	0.001	0.126
Multisite Pca presentation	14453	3561.81	0.000	0.000	0.005	0.970
Metastatic Pca presentation	425	778.05	0.585	-0.002	0.001	0.039
Unstaged Pca presentation	-858	596.46	0.151	-0.001	0.001	0.107
Metro resident	3459	476.41	0.000	0.002	0.001	0.011
% with college degree by Zip Code	42	14.81	0.005	0.000	0.000	0.551
Mean income by Zip Code	0	0.012	0.004	0.000	0.000	0.677
Detroit	3512	682.74	0.000	0.001	0.001	0.545
Hawaii	806	1224.72	0.510	0.006	0.002	0.003
Iowa	-11530	689.29	0.000	0.003	0.001	0.004
New Mexico	-6654	957.40	0.000	0.007	0.001	0.000
Seattle	-12389	725.13	0.000	0.004	0.001	0.001
Utah	-13252	851.35	0.000	0.003	0.001	0.022
Atlanta Metro	-4976	943.72	0.000	0.000	0.001	0.917
Rural Georgia	-4571	2575.33	0.076	-0.005	0.004	0.169
Kentucky	-8461	988.50	0.000	0.004	0.002	0.017
Louisiana	-9242	1036.92	0.000	0.004	0.002	0.024
New Jersey	10040	796.75	0.000	0.000	0.001	0.780
California	2202	601.64	0.000	0.002	0.001	0.018
Expenditure in '000				0.001	0.000	0.016
Year of Diagnosis =1						
Year 93				1.795	0.001	0.000
Year 94				-4.205	0.001	0.000
Year 95				-13.455	0.001	0.000
Year 96				-23.075	0.001	0.000
Year 97				-36.425	0.001	0.000
Year 98				-48.196	0.001	0.000
Year 99				-55.206	0.001	0.000
Year 00				-64.556	0.001	0.000
Year 01				-73.306	0.001	0.000
Year 02				-81.016	0.001	0.000
Constant	90495	4403.312	0.000	290.671	0.007	0.000

Table B8. Full equation results from the simultaneous equation model
(Table 3.3 Average of second year outcome as the variable of interest)

	Equation 1 Dependent Variable=Expenditure			**Equation 2** Dependent Variable=Outcome year 1		
	Coef.	**Std. Err.**	**P>z**	**Coef.**	**Std. Err.**	**P>z**
Outcome—Year 2	-186	4.95	0.000			
Therapy started	20029	391.98	0.000			
Age	-478	27.37	0.000	-0.0004	0.0002	0.015
Charlson Score	1525	75.61	0.000	0.000	0.001	0.612
Race-Black	377	543.83	0.489	0.002	0.003	0.573
Race--Other	33	651.12	0.960	0.006	0.004	0.127
Multisite Pca presentation	14436	3562.73	0.000	0.001	0.021	0.970
Metastatic Pca presentation	398	778.26	0.609	0.009	0.004	0.040
Unstaged Pca presentation	-856	596.97	0.152	0.006	0.003	0.107
Metro resident	3377	476.41	0.000	-0.007	0.003	0.011
% with college degree by Zip Code	42	14.81	0.005	0.000	0.000	0.550
Mean income by Zip Code	0	0.012	0.004	0.000	0.000	0.676
Detroit	3601	682.82	0.000	-0.002	0.004	0.548
Hawaii	844	1225.06	0.491	-0.021	0.007	0.003
Iowa	-11560	689.46	0.000	-0.012	0.004	0.004
New Mexico	-6657	957.65	0.000	-0.027	0.006	0.000
Seattle	-12323	725.27	0.000	-0.015	0.004	0.001
Utah	-13215	851.57	0.000	-0.012	0.005	0.022
Atlanta Metro	-4940	943.96	0.000	0.001	0.005	0.915
Rural Georgia	-4636	2576.01	0.072	0.020	0.015	0.169
Kentucky	-8001	987.04	0.000	-0.014	0.006	0.018
Louisiana	-8811	1035.73	0.000	-0.014	0.006	0.025
New Jersey	10553	794.25	0.000	-0.001	0.005	0.798
California	2391	601.35	0.000	-0.008	0.004	0.019
Expenditure in '000				-0.003	0.001	0.016
Year of Diagnosis =1						
Year 93				-5.602	0.004	0.000
Year 94				-14.852	0.004	0.000
Year 95				-24.471	0.004	0.000
Year 96				-37.820	0.004	0.000
Year 97				-49.589	0.004	0.000
Year 98				-56.598	0.004	0.000
Year 99				-65.948	0.004	0.000
Year 00				-74.697	0.004	0.000
Year 01				-82.406	0.004	0.000
Year 02				-95.076	0.004	0.000
Constant	83565	4357.18	0.000	292.135	0.025	0.000

Table B9. Full equation results from the simultaneous equation model
(Table 3.3 Third year outcome as the variable of interest)

	Equation 1 Dependent Variable=Expenditure			**Equation 2** Dependent Variable=Outcome year 1		
	Coef.	**Std. Err.**	**P>z**	**Coef.**	**Std. Err.**	**P>z**
Outcome—Year 3	-179	4.8	0.00			
Therapy started	20053	392.1	0.000			
Age	-476	27.4	0.000	0.001	0.001	0.015
Charlson Score	1516	75.6	0.000	-0.001	0.002	0.613
Race-Black	361	543.9	0.507	-0.006	0.010	0.573
Race--Other	5	651.3	0.994	-0.018	0.012	0.127
Multisite Pca presentation	14443	3563.3	0.000	-0.002	0.065	0.970
Metastatic Pca presentation	376	778.4	0.629	-0.029	0.014	0.040
Unstaged Pca presentation	-869	597.2	0.146	-0.017	0.011	0.108
Metro resident	3349	476.5	0.000	0.022	0.009	0.011
% with college degree by Zip Code	41	14.8	0.005	0.000	0.000	0.550
Mean income by Zip Code	0	0.0	0.004	0.000	0.000	0.677
Detroit	3658	682.9	0.000	0.008	0.013	0.549
Hawaii	887	1225.3	0.469	0.066	0.022	0.003
Iowa	-11560	689.6	0.000	0.038	0.013	0.004
New Mexico	-6611	957.8	0.000	0.085	0.018	0.000
Seattle	-12270	725.3	0.000	0.047	0.014	0.001
Utah	-13177	851.7	0.000	0.037	0.016	0.022
Atlanta Metro	-4923	944.1	0.000	-0.002	0.017	0.915
Rural Georgia	-4676	2576.4	0.070	-0.064	0.047	0.169
Kentucky	-7772	986.5	0.000	0.044	0.018	0.018
Louisiana	-8579	1035.2	0.000	0.043	0.019	0.025
New Jersey	10797	793.3	0.000	0.004	0.016	0.798
California	2497	601.2	0.000	0.027	0.011	0.019
Expenditure in '000				0.009	0.004	0.016
Year of Diagnosis =1						
Year 93				-10.508	0.012	0.000
Year 94				-20.128	0.012	0.000
Year 95				-33.480	0.013	0.000
Year 96				-45.253	0.013	0.000
Year 97				-52.265	0.013	0.000
Year 98				-61.618	0.013	0.000
Year 99				-70.370	0.013	0.000
Year 00				-78.081	0.012	0.000
Year 01				-90.755	0.013	0.000
Year 02				-98.557	0.013	0.000
Constant	80060	4336.1	0.000	287.569	0.079	0.000

Table B10. Full equation results from the simultaneous equation model
(Table 3.3 Fourth year outcome as the variable of interest)

	Equation 1 Dependent Variable=Expenditure			**Equation 2** Dependent Variable=Outcome year 5		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Outcome—Year 4	-180	4.93	0.000			
Therapy started	20061	392.26	0.000			
Age	-474	27.37	0.000	0.002	0.001	0.015
Charlson Score	1506	75.61	0.000	-0.002	0.003	0.614
Race-Black	369	544.04	0.497	-0.009	0.015	0.572
Race--Other	6	651.43	0.993	-0.028	0.018	0.126
Multisite Pca presentation	14430	3564.12	0.000	-0.004	0.100	0.970
Metastatic Pca presentation	339	778.54	0.663	-0.045	0.022	0.040
Unstaged Pca presentation	-940	597.36	0.115	-0.027	0.017	0.109
Metro resident	3332	476.65	0.000	0.034	0.013	0.011
% with college degree by Zip Code	41	14.82	0.005	0.000	0.000	0.550
Mean income by Zip Code	0	0.012	0.004	0.000	0.000	0.677
Detroit	3700	683.00	0.000	0.012	0.019	0.550
Hawaii	905	1225.58	0.460	0.102	0.034	0.003
Iowa	-11544	689.73	0.000	0.058	0.020	0.004
New Mexico	-6584	958.09	0.000	0.130	0.027	0.000
Seattle	-12223	725.48	0.000	0.072	0.021	0.001
Utah	-13144	851.90	0.000	0.057	0.025	0.022
Atlanta Metro	-4890	944.33	0.000	-0.003	0.026	0.915
Rural Georgia	-4645	2577.02	0.071	-0.099	0.072	0.169
Kentucky	-7693	987.04	0.000	0.067	0.029	0.018
Louisiana	-8458	1035.50	0.000	0.066	0.029	0.025
New Jersey	10905	793.98	0.000	0.006	0.024	0.798
California	2552	601.33	0.000	0.041	0.017	0.019
Expenditure in '000				0.013	0.005	0.016
Year of Diagnosis =1						
Year 93				-11.560	0.018	0.000
Year 94				-24.910	0.019	0.000
Year 95				-36.683	0.020	0.000
Year 96				-43.696	0.020	0.000
Year 97				-53.051	0.020	0.000
Year 98				-61.805	0.020	0.000
Year 99				-69.518	0.020	0.000
Year 00				-82.190	0.018	0.000
Year 01				-89.996	0.019	0.000
Year 02				-96.279	0.021	0.000
Constant	78389	4330.54	0.000	278.909	0.122	0.000

Table B11. Full equation results from the simultaneous equation model
(Table 3.3 Fifth year outcome as the variable of interest)

	Equation 1 Dependent Variable=Expenditure			**Equation 2** Dependent Variable=Outcome year 5		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Outcome—Year 5	-185	5.07	0.000			
Therapy started	20070	392.27	0.000			
Age	-474	27.37	0.000	0.002	0.001	0.015
Charlson Score	1507	75.61	0.000	-0.002	0.003	0.614
Race-Black	359	544.03	0.509	-0.009	0.016	0.573
Race--Other	-8	651.42	0.990	-0.029	0.019	0.127
Multisite Pca presentation	14441	3564.0	0.000	-0.004	0.104	0.970
Metastatic Pca presentation	340	778.52	0.662	-0.047	0.023	0.040
Unstaged Pca presentation	-982	597.11	0.100	-0.028	0.017	0.109
Metro resident	3311	476.56	0.000	0.036	0.014	0.011
% with college degree by Zip Code	41	14.82	0.005	0.000	0.000	0.550
Mean income by Zip Code	0	0.012	0.004	0.000	0.000	0.677
Detroit	3696	682.98	0.000	0.012	0.020	0.549
Hawaii	883	1225.5	0.471	0.106	0.036	0.003
Iowa	-11565	689.71	0.000	0.060	0.021	0.004
New Mexico	-6604	958.05	0.000	0.136	0.028	0.000
Seattle	-12224	725.46	0.000	0.075	0.022	0.001
Utah	-13158	851.88	0.000	0.059	0.026	0.022
Atlanta Metro	-4882	944.29	0.000	-0.003	0.027	0.914
Rural Georgia	-4651	2577.0	0.071	-0.103	0.075	0.169
Kentucky	-7610	986.44	0.000	0.070	0.030	0.018
Louisiana	-8397	1035.1	0.000	0.068	0.031	0.025
New Jersey	10999	793.00	0.000	0.006	0.025	0.800
California	2575	601.22	0.000	0.043	0.018	0.019
Expenditure in '000				0.014	0.006	0.016
Year of Diagnosis =1						
Year 93				-15.368	0.018	0.000
Year 94				-27.138	0.020	0.000
Year 95				-34.150	0.020	0.000
Year 96				-43.504	0.021	0.000
Year 97				-52.259	0.021	0.000
Year 98				-59.973	0.021	0.000
Year 99				-72.647	0.021	0.000
Year 00				-80.449	0.019	0.000
Year 01				-86.734	0.020	0.000
Year 02				-96.098	0.022	0.000
Constant	77841	4325.805	0.000	269.356	0.127	0.000

Table B12. Full equation results from the simultaneous equation model
(Table 3.3 Average of first to fifth year outcome as the variable of interest)

	Equation 1 Dependent Variable=Expenditure			Equation 2 Dependent Variable=Outcome average of year 1-5		
	Coef.	Std. Err.	P>z	Coef.	Std. Err.	P>z
Outcome—average of year 1-5	-188	5.04	0.000			
Therapy started	20044	392.06	0.000			
Age	-477	27.37	0.000	0.001	0.000	0.015
Charlson Score	1521	75.61	0.000	-0.001	0.002	0.612
Race-Black	373	543.88	0.492	-0.004	0.008	0.573
Race--Other	19	651.20	0.977	-0.014	0.009	0.127
Multisite Pca presentation	14431	3563.1	0.000	-0.002	0.051	0.970
Metastatic Pca presentation	386	778.32	0.620	-0.023	0.011	0.040
Unstaged Pca presentation	-872	597.07	0.144	-0.014	0.009	0.108
Metro resident	3379	476.50	0.000	0.017	0.007	0.011
% with college degree by Zip Code	42	14.81	0.005	0.000	0.000	0.550
Mean income by Zip Code	-0.04	0.012	0.004	0.000	0.000	0.677
Detroit	3623	682.86	0.000	0.006	0.010	0.548
Hawaii	874	1225.2	0.476	0.052	0.017	0.003
Iowa	-11550	689.52	0.000	0.029	0.010	0.004
New Mexico	-6614	957.77	0.000	0.066	0.014	0.000
Seattle	-12291	725.31	0.000	0.037	0.011	0.001
Utah	-13187	851.65	0.000	0.029	0.013	0.022
Atlanta Metro	-4934	944.05	0.000	-0.001	0.013	0.915
Rural Georgia	-4645	2576.2	0.071	-0.050	0.037	0.169
Kentucky	-7954	987.19	0.000	0.034	0.014	0.018
Louisiana	-8743	1035.8	0.000	0.033	0.015	0.025
New Jersey	10603	794.46	0.000	0.003	0.012	0.793
California	2428	601.35	0.000	0.021	0.009	0.019
Expenditure in '000				0.007	0.003	0.016
Year of Diagnosis =1						
Year 93				-8.248	0.009	0.000
Year 94				-18.246	0.010	0.000
Year 95				-28.448	0.010	0.000
Year 96				-38.670	0.010	0.000
Year 97				-48.718	0.010	0.000
Year 98				-57.638	0.010	0.000
Year 99				-66.738	0.010	0.000
Year 00				-75.995	0.009	0.000
Year 01				-84.639	0.010	0.000
Year 02				-93.405	0.011	0.000
Constant	82207	4349.785	0.000	283.728	0.062	0.000

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ABSTRACT

MEASURING THE EFFECT OF TECHNOLOGICAL CHANGE IN HEALTH CARE COST AND EXPENDITURE

by

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Advisor: Dr. Allen C. Goodman

Major: Economics

Degree: Doctor of Philosophy

Technological change has a major role in driving up health care cost and expenditure. Yet we are not fully able to know the extent to which technological change affects cost and expenditure and the way new technologies enter the cost or expenditure functions. This paper uses historical data of US elderly males to see how health care spending associated with prostate cancer treatment behaves over time. Understanding the extent and mechanism by which a new technology actually translates into higher cost are main objectives of this study.

Study design, data and organization of the report:

This study uses a retrospective research design with observational historical data. The subjects are Medicare enrolled individuals aged 65 or above who were diagnosed with prostate cancer from 1991 to 2002. SEER Medicare-linked database is used in the study. In Chapter 2, I present a long run view of health care spending growth. Spending associated with prostate cancer care was calculated by diagnosis, diagnosis and treatment and method of treatment status. Chapter 3 uses outcome as a single measure of technological change. Prostate cancer caused death rate is used as the key outcome in this regard. The last key chapter is Chapter 4, which is focused on the two innovations in external beam radiation therapy. Of main interest is whether the incremental spending caused by new treatments grows over time. Two innovations in radiation therapy, 3D-CRT and IMRT, are examined.

Major findings and conclusions:

The average first year incremental spending following an individual's diagnosis of prostate cancer increased from $31,000 in 1993 to $66,000 in 2002, which is 113%. The increase in expenditure associated with the diagnosis and treatment was from $48,018 to $85,267 (80%) during the same period. The findings suggest a substantial increase in health care expenditure that is explained by the changes in prostate cancer care during the study period. If all changes are loosely defined as technological changes, then technological change in the first year of prostate cancer care alone contributed about 100 percent increase in expenditure in

10 years' period. There were more substantial changes in treatment options than in overall care. Among treatment options, surgery saw the highest and the fastest growth of spending.

The estimates using the death rate as a proxy measure of technological change show that the cost per patient would add to $19,055 for the entire decline in death rate caused by prostate cancer. It also meant avoiding one prostate cancer related death in the 65 and older age group would cost $185,000 in the first year of care only. The findings imply that avoiding a death from PCa gave about 7 additional life years in the period. The first year cost of additional life year from this perspective is about $26,000.

Finally, estimates show that one year average costs were $8,627 and $11,836 higher than SRT for 3D-CRT and 3D-CRT and IMRT combined respectively. Similarly, two year cost differentials were $12,242 and $14,724 higher for 3D-CRT and 3D-CRT and IMRT combined respectively. The findings show that incremental spending of 3D-CRT rose consistently for a certain period before it started subsiding. Estimates that included both 3D-CRT and IMRT show that incremental spending did not subside but kept increasing after IMRT was introduced. It is found that the incremental cost of new technology rises as the acceptance of that technology gains momentum. This suggests that technology also enters cost and expenditure functions through the strategic plans of health care providers, primarily hospitals. Therefore the role of new technologies to drive up cost and

spending at least partly depends on the technology adoption behavior of the health care providers, such as who adopts the new technology first.

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