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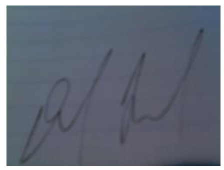
Physicians' Decision Choice of Conservative Treatment Impacted by Evidence, Peers, and Financial Incentives

By

Yu Liu
Doctor of Philosophy

Health Policy and Economics



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An abstract of
A dissertation submitted to the Faculty of the James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
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Abstract

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Yu Liu

Active Surveillance had become an increasingly popular disease management strategy for localized prostate cancer between 2001 and 2015. Using active surveillance, rather than other active treatments, for localized prostate cancer patients presented opportunities for health care cost saving. Urologists were gradually adopting active surveillance. In my dissertation, I studied the adoption of active surveillance from three perspectives: urologists' referral network position, peer influence, and financial influence. I also compared the use of active surveillance with common active treatments, e.g., prostatectomy and intensity modulated radiation therapy. I found that urologists who were at the center of the referral network were more likely to use active surveillance than urologists who were at the periphery of the referral network. I also found that the patients' selection criteria of peers had different impacts for active surveillance, prostatectomy, and intensity modulated radiation therapy. Lastly, the reimbursement reduction of active treatments reduced urologists' use of conservative treatment, and the impacts were different for urologists who used different kinds of treatments as their major treatment methods. My research results had three key health policy implications. In the era of precision medicine, patients were more likely to undertake diversified treatment strategies, including conservative treatment methods for low risk cancer. Primary care doctors and specialists who were at the center of the referral network may disseminate information about the efficacy of conservative treatments. Therefore, policy makers may leverage their influence to promote cost effective conservative treatments. Second, policy makers may consider introducing patients' selection criteria measurements as a physician performance evaluation method. Third, the Centers for Medicare and Medicaid Services shall consider the impacts of reimbursement cut of active treatments on the promotion of conservative treatments, and consider financial incentives to promote conservative treatment.

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Contents

List of Figures

List of Tables

List of Supplementary Files

1 Introduction

1.1 Overview of Conservative Treatment for Localized Prostate Cancer

1.1.1 Localized Prostate Cancer and Treatment

Localized prostate cancer is a major health issue for men in the United States. In 2017, prostate cancer accounted for about 20% of newly reported cancer cases (not including nonmelanoma skin cancer) among male Americans (Henley et al. 2020). One in 41 men died of prostate cancer in 2019, which was the second leading cause of cancer death (after lung cancer) for male Americans (Cancer.org 2020). About 90% of prostate cancers were diagnosed at local or regional stage (Cancer.net 2019). The average age of US men diagnosed with prostate cancer is 66 (Cancer.org 2020), and most early prostate cancers have an indolent period of 10 to 15 years (Johansson et al. 2004, Popiolek et al. 2013). Patients with low risk localized prostate cancer may have a lower all-cause mortality rate than cancer-free population (Van Hemelrijck et al. 2016).

Common active treatment options for localized prostate cancer include surgery (prostatectomy), radiation therapies (e.g., intensity-modulated radiation therapy [IMRT], brachytherapy, and three-dimensional conformal radiation therapy), androgen deprivation therapy, and cryotherapy (Mohler 2010). The National Comprehensive Cancer Network (NCCN) recommended active surveillance as a treatment for localized prostate cancer in 2010 (Mohler 2010). Different treatment options for localized prostate cancer may have different impacts on disease progression (Hamdy et al. 2016) and different side effects (Hoffman et al. 2020). Different kinds of treatments generate different revenue for providers, and the population treatment patterns impact the health expenditures of the health system (Nguyen et al. 2011, Trogdon et al. 2018, Wilson et al. 2007). There is uncertainty about the tradeoffs between disease progression, life expectancy, side effects, and cost between different treatment options (Sun, Oyesanmi et al. 2014) and the cost-effectinvess of different kinds of treatmnet (Harat, Harat, and Martinson 2020). Table 1 summarizes the treatment costs for different localized prostate cancer treatment options.

1.1.2 Trends of Localized Prostate Cancer Diagnosis and Treatments

Early stage prostate cancer are normally detected by screening, such as prostate-specific antigen (PSA) blood test or a digital rectal exam (DRE) (Cancer.org 2021). Like other kinds of cancer, pre-treatment localized prostate cancer risk stratification include prognostic factors such as PSA value, clinical stages, and Gleason score (Rodrigues et al. 2012). Gleason score is a major criteria for prostate cancer risk stratification (Rodrigues et al. 2012) and is the best independent indicator for clinical prognosis (Rubin, Girelli, and Demichelis 2016, Martin et al. 2011).

PSA screening for early prostate cancer detection has become popular since late 1980s (Hoffman et al. 2016). Professional associations, e.g., United States Preventive Services Task Force (USPSTF), the American Urological Association (AUA), and the American Cancer Society (ACS) changed guidelines to discourage routine use of PSA screening for prostate cancer since 1990s, because of potential over-diagnosis and over-treatment (Hoffman et al. 2016, Howard et al. 2013). The guidelines changes contributed to the decreasing incidence rate of localized prostate cancer since 2001 (Hoffman et al. 2016, Herget et al. 2016). Figure 1 summarizes the timelines for important clinical guidelines related to prostate cancer screening, treatment, and clinical trials.

1.1.3 Active Surveillance Treatment for Localized Prostate Cancer

Active surveillance (or expectant management) is effective disease management approach for localized prostate cancer patients (Filson, Marks, and Litwin 2015, Garisto and Klotz 2017), and has been included into NCCN's 2010 guideline as a prostate cancer disease management strategy for low- and intermediate- risk patients (Mohler 2010). The expectation of life is 11.2 years for 75-year-old American men as of 2015 (CDC 2018) and the 2010 National Comprehensive Cancer Network (NCCN) guideline recommended that the life expectancy of 10 years is the threshold of treatment and active surveillance versus observation for low risk prostate cancer patients (Mohler 2010). Table 2 summarizes the National Comprehensive Cancer Network (NCCN) 2010 guidelines for localized prostate cancer treatment options.

The use of active surveillance for localized prostate cancer has been increasing between 2004 and 2015 (Liu et al. 2020, Ritch et al. 2015, Weiner et al. 2015). Figure 2 shows the trends of different treatment options for newly diagnosed localized prostate cancer between 2004 and 2015. Previous research reported patients' characteristics that associated with the increasing adoption of active surveillance between 2004 and 2015 (Burt, Shrieve, and Tward 2018, Butler et al. 2019, Weiner et al. 2015, Ritch et al. 2015), but the decision of undertaking active surveillance was mainly influenced by physicians (Gorin et al. 2011, Cutler et al. 2018, Finkelstein, Gentzkow, and Williams 2016). Variations of the usage of active surveillance existed among different urologists (Tyson et al. 2017), different practices (Womble et al. 2015, Aizer et al. 2012, Modi et al. 2019), and different regions (Filson et al. 2014).

1.2 Physician Treatment Decision Choice

Academic research to understand physicians' treatment decision has a long history. Evan et al. (Evans 1974) published one of the earliest academic research introducing the theory and concept of physician induced demand. Fuchs (Fuchs 1978), and Cromwell and Mitchell (Cromwell and Mitchell 1986) provided further empirical evidences. However, few empirical evidence for physician induced demand were quantified (Dranove and Wehner 1994, Hay and Leahy 1982, Sloan and Feldman 1978, Feldman and Sloan 1988). McGuire (McGuire 2000) and Johnson (Johnson 2014) provided detailed reviews for theoretical models and empirical evidence. Researchers also had evaluated physicians' responses to the reimbursement fee changes, in order to examine whether physicians changed their service quantity and complexity when facing a reducing revenue (Gruber and Owings 1996, Gruber, Kim, and Mayzlin 1999, Christensen 1992, Gabel and Rice 1985, Nguyen and Derrick 1997, Yip 1998). Some studies found no evidence that physicians increase service volume or intensity to offset potential revenue loss (Lee and Mitchell 1994b, Hadley et al. 2009, Rice 1983, Keeler and Fok 1996).

Nevertheless, treatment variations existed among different regions, and between different physicians (Skinner 2011). Factors, such as training (Phelps and Mooney 1993, Doyle, Ewer, and Wagner 2010), practice environment and influence from peers (Molitor 2018, Agha and Molitor 2018, Lucas et al. 2010, Bradley et al. 2005, Coleman, Katz, and Menzel 1957, Iyengar, Van den Bulte, and Valente 2011, Donohue et al. 2018, Agha and Zeltzer 2019, Keating et al. 2020), and productivity and expertise (Chandra and Staiger 2007, Skinner and Staiger 2015, Currie and MacLeod 2017) may contribute to the variations. Some recent research had suggested that physicians' personal practice style was one of the major reasons for the treatment variations (Cutler et al. 2018, Finkelstein, Gentzkow, and Williams 2016, Epstein and Nicholson 2009, Dranove, Ramanarayanan, and Sfekas 2011, Grytten and Sorensen 2003, Abaluck et al. 2016, Currie, MacLeod, and Van Parys 2016, Currie and MacLeod 2017, Lipitz-Snyderman et al. 2016).

Specific factors that may also change an individual physician's preferred treatment method, reduce the usage of a type of treatment, or de-adopt a specific treatment method. These factors include clinical evidence (Hersh, Stefanick, and Stafford 2004, Howard et al. 2011, Howard, Brophy, and Howell 2012, Howard and Shen 2014, Howard et al. 2016, Dorsey et al. 2010, Duffy and Farley 1992, Dotan et al. 2014), the financial incentives, particularly inherent in private institute and inherent in self-referral physicians (Howard, David, and Hockenberry 2017, Baker 2010, Mitchell and Sunshine 1992, Mitchell 2013, Shah et al. 2011), and an adverse event (Choudhry et al. 2006).

1.3 Physicians' De-adoption of Low-value Care and Adoption of Conservative Treatment

Physicians' de-adoption of low value care is slow (Roman and Asch 2014). Niven et al. (Niven, Mrklas, et al. 2015) and Colla et al. (Colla et al. 2017) summarized interventions on reducing utilization of low-value care. Clinical evidence and guidelines remain one of the important interventions to reduce low value care. Studies that report physicians' responses to negative clinical trials results have mixed findings. Some studies found that physicians reduced the use of the treatment after negative trial results or guideline changes (Howard, Brophy, and Howell 2012, Howard et al. 2016, Duffy and Farley 1992, Howard and Shen 2014, Dotan et al. 2014, Hersh, Stefanick, and Stafford 2004, Dorsey et al. 2010, Howard et al. 2011, Howard et al. 2013). However, some studies showed that clinical evidence and guidelines had limited impact on physicians previous practice pattern (Deyell et al. 2011, Howard and Shen 2012, Howard, David, and Hockenberry 2017, Shen et al. 2013, Smieliauskas, Lam, and Howard 2014, Niven, Rubenfeld, et al. 2015, Abrishami, Boer, and Horstman 2019, Howard and Adams 2012). Clearer and convincing clinical research evidence are critical for de-adoption of low value care (Howard and Gross 2015). Researchers had championed the de-adoption of low value services to reduce overall healthcare expenditures (Schwartz et al. 2014). However, few studies have investigated the adoption of conservative treatments (Modi et al. 2019), and whether conservative treatment can reduce healthcare expenditures (van de Graaf et al. 2016, O'Donoghue et al. 2008).

1.4 Motivations

1.4.1 The Adoption Pattern of Conservative Treatment: Active Surveillance

The adoption patterns of conservative treatment, e.g., active surveillance for localized prostate cancer by urologists, may not be the same as the adoption patterns of a new technology. First, active surveillance is not a new technology for localized prostate cancer treatment that need urologists to invest in new equipment or acquire new knowledge. The Scandinavia clinical trial reported prostatectomy and watchful waiting treatment strategy has equivalent mortality rate for patients who were 65 years and older in 2002 and 2005 (Bill-Axelson et al. 2005, Holmberg et al. 2002). Watchful waiting for localized prostate cancer was a popular treatment approach in the 1970s and 1980s before the PSA test became more widely used (Coen et al. 2011). Therefore, updated medical knowledge, facility location, and capital investment are not barriers for adoption of active surveillance for localized prostate cancer.

Second, payments of active surveillance is less than other popular treatments for localized prostate cancer, therefore use of active surveillance will reduce urologists' revenue. Active surveillance for localized prostate cancer is an exnovation that may substitute the usage of other cutting-edge technologies, such as robotic prostatectomy, proton radiotherapy or Intensity-modulated radiation therapy (IMRT). Medicare payments for active surveillance as the initial disease management approach for localized prostate cancer was about 1/8 of the payments of IMRT and about ¼ of the payments of prostatectomy. (Table 1). The adoption of active surveillance for localized prostate cancer is slower than the adoption of IMRT between 2004 and 2015. For example, from 2004-2005 to 2010-2011, the estimated probability of undertaking active surveillance for patients aged 75 and above with intermediate risk localized prostate cancer had increased from 11.6% to 14.6%, and the estimated probability of undertaking IMRT increased from 29.7% to 36.0% (Liu et al. 2020). Though radiation oncologists rather than urologists received the reimbursement of IMRT treatment for localized prostate cancer, the differences of payments may be an important reason.

Innovative treatments are normally more expensive than existing therapies (Newhouse 1992, Weisbrod 1991). Most of the studies investigated innovative treatments rather than conservative treatments. Cutler and Huckman (Cutler and Huckman 2003) studied the impact of percutaneous transluminal coronary angioplasty (PTCA) diffusion on coronary artery bypass graft surgery (CABG). PTCA was less expensive than CABG, but more expensive than the conservative management of coronary artery disease. The diffusion of PTCA may not reduce overall health expenditure of coronary artery disease because the expense saved was off-set by the increasing usage of PTCA and decreasing usage of conservative management of disease (Cutler and Huckman 2003). The study of active surveillance for localized prostate cancer is different from the study of PTCA. For example, PTCA was mainly practiced by cardiologists, and CABG was mainly practiced by cardiothoracic surgeons. However, active surveillance can be practiced by all urologists.

Third, though the NCCN introduced active surveillance as a treatment approach for localized prostate cancer, clinical evidence was not clear for the cost-effectiveness of active surveillance compared to other active treatments (Amin, Sher, and Konski 2014). There were no clinical trial results that undermine the efficacy of exiting popular treatment options. Therefore, the decision of urologists to use active surveillance was mainly because of their personal intrinsic concerns for the value of care for patients.

1.4.2 Implications for Healthcare System Cost

The increasing healthcare cost in the United States had been and will continue to be challenges (Papanicolas, Woskie, and Jha 2018, Bauchner and Fontanarosa 2018, Baicker and Chandra 2018). Using active surveillance as initial disease management approach instead of immediate definitive treatment among low-risk prostate cancer patients presents significant opportunities for healthcare cost saving in the US (Trogdon et al. 2018). Further understanding the adoption pattern and factors that influencing the adoption of conservative treatment will provide evidence and policy implications for reducing the overall healthcare cost in the United States.

1.5 Dissertation Outlines

In my dissertation, I will investigate the adoption of active surveillance for localized prostate cancer by urologists between 2001 and 2015. I will explore this topic from different perspectives in the three chapters described below. In Chapter Two, I will explore how urologist's referral network position influence their adoption of active surveillance. In Chapter Three, I will evaluate the impact of peers on urologists' choices of active surveillance. In Chapter Four, I will study how the potential loss of revenue impact urologists' use of active surveillance.

1.6 Innovations

First, we propose to study an exnovation in healthcare, which received less attention than innovation (Greenhalgh et al. 2004). Previous research studies on adoption or diffusion of practices in healthcare setting mainly focused on new technologies, for example, new drugs (Agha and Molitor 2018) or new surgical techniques (Vanderveen et al. 2007). Few studies are focusing on exnovation (Bekelis et al. 2017, Rodriguez et al. 2016), and little is known about the patterns and the model of exnovation (Roman and Asch 2014, Davidoff 2015).

Second, I tried to understand the impact of peers and environment (Chapter Three) on physicians' use of a conservative treatment method. Most of the current studies related to peer and environment influence (Molitor 2018), and personal practice style (Currie, MacLeod, and Van Parys 2016, Epstein and Nicholson 2009) used active treatment as study objects. I further illustrated whether the impact of peers are the same for active treatment and conservative treatment methods (Chapter Three).

Third, I proposed to use urologists' referral network position as the main independent variable and measure its impact on adoption of active surveillance (Chapter Two). Few studies had investigated physicians' behaviors using referral network.(Agha et al. 2018, Moen et al. 2018).

Fourth, I separated the impact of patients' volume change and payment change on physicians' choices of different types of treatments (Chapter Four). Both patients' volume fluctuation and reimbursement payment changes may influence physicians' revenue and profit. Physicians may switch between different kinds of treatments for localized prostate cancer to recoup their potential revenue loss. Previous research focused on either volume change or payment changes. The simultaneous changes of patients' volume (because of screening guideline changes) and payment for localized prostate cancer (because of reimbursement changes) allow me to study the impact of both factors on the same group of physicians.

Fifth, I used administrative dataset (SEER-Medicare) to measure physicians' referral network, practice location, and affiliations. In addition, I proposed an approach to measure physicians' practice style when multiple treatment options are available. Specifically, I proposed a method using Kullback-Leibler (KL) Distance to measure how a urologist's patient selection for a specific treatment is different from the market average.

2 Physician Referral Network Position and Decision Choice

2.1 Background

2.1.1 Physician Network Position and Adoption of Treatments

Physicians' positions in a network are associated with the information they receive, and their adoption of new technology and evidence-based medicine. Studies reported that physicians who had more connections outside their work network (e.g., their department or institute) were more likely to use the emerging evidence-based clinical practice (Mascia, Cicchetti, and Damiani 2013, Fattore et al. 2009, Mascia and Cicchetti 2011), were more likely to adopt electronic medical record system (Sykes, Venkatesh, and Rai 2011), and less more likely to share similar practice styles (Pollack et al. 2012, Landon et al. 2012, Fattore et al. 2009). Healthcare professionals who had more network connections outside their work network also helps knowledge to transfer across different specialties (Tasselli 2015). Donohue et al. (Donohue et al. 2018) reported that physicians' network established by shared patients is more effective than their work network to promote a new drug adoption. Landon et al., (Landon et al. 2018) reported that physicians who had more connections to other physicians through shared patients had higher healthcare expenses and utilization. Funk et al., (Funk et al. 2018) used specialists' interactions within the same specialist and with primary care doctors as a measure of specialist's informal integration with primary care doctors. The authors found that higher integration outside specialty is associated with lower healthcare cost. Hussain et al., (Hussain et al. 2015) reported that informal collaborations between surgeons and oncologists measured by shared patients is associated with lower stage III colon cancer mortality. Using claim-based data of 2004-2005, Pollack et al. (Pollack et al. 2012) found that urologists within a subgroup by shared patients were more likely to use same treatment approach, e.g., prostatectomy. Locus et al. reported that the approach a colleague test and treat patients is associated with cardiologists' propensity to use the same method.(Lucas et al. 2010) Moen et al. studied both hospital network and physician network, and didn't find physicians' peers have significant impact on implantable cardioverter defibrillator therapy guideline compliance (Moen et al. 2018, Moen et al. 2016).

2.1.2 Current Challenges Evaluating Networks' Impact on Treatment Adoption

There remain issues when evaluating network's impact on physicians' choices of treatment. First, many studies of network impact used a network by shared patients. However, physicians who shared patients were more likely to practice in the same practice or were more likely to be affiliated with a common academic institute (Barnett, Landon, Keating, et al. 2011). Therefore, it may be difficult to differentiate the impact of network position and the impact of the overall practice environment. Second, research investigating the impact of physicians' network position on their treatment choices may not be able to fully consider the practice style within the network. For example, if we evaluated the impact of a network on physicians' treatment choice. If most of the physicians in this network were connected with each other and had higher usage of a treatment method, the results illustrating the impact of network scores is biased upwards. Indeed, Pollack et al. (Pollack et al. 2012) showed that physicians within small subgroups tended to share similar practice style.

2.1.3 Physician's Network Established by Primary Care Doctors

Given the issues above, I propose to establish a physicians' referral network by primary care doctors. There are two potential information transmission mechanisms that may promote the active surveillance for localized prostate cancer within the referral network we propose. First, primary care doctors may serve as an "information hub" to disseminate cost-effective practices. Physicians who shared patients have high probability of exchanging information (Barnett, Landon, Keating, et al. 2011, Song, Sequist, and Barnett 2014, Landon et al. 2012). In addition, studies reported that primary care physicians participated in cancer treatment decisions. Klabunde et al. reported that over 50% of the primary care reported participating treatment preference and decision for cancer patients (Klabunde et al. 2009). Jang et al. showed that patients' primary care visit after diagnosis of localized prostate cancer is associated with usage of active surveillance (Jang et al. 2010). By national survey, Radhakrishnan et al. (Radhakrishnan et al. 2021) showed that primary care doctors were increasing involved in low risk cancer care decisions. Agha et al. (Agha et al. 2018) showed that the patients treated by primary care doctors who worked closely with few specialists had lower overall healthcare cost. Second, patients may discuss with urologists about the active surveillance option after hearing such option from primary care doctor or other resources. A VA trial reported that patients' activation intervention increased patients' discussion with their doctors regarding drug usage guidelines (Kaboli et al. 2018).

The other potential mechanism is the reputation and peer pressure. The reputation and peer pressure effect may be more salient in a health service area with a denser network, e.g., more urologist connected with each other by referral networks. A denser network structure promotes socially accepted behaviors (Raub and Weesie 1990, Lippert and Spagnolo 2011). Primary care doctors may intentionally refer patients who were potential candidates for active surveillance treatment to urologists with a reputation of diversified treatment approaches. In the era of personalized medicine, physicians may also intentionally diversify their treatment option portfolio because of both the extrinsic general trends of personalized medicine usage (Jameson and Longo 2015) and intrinsic reputation concern among the physicians' community (Amol Navathe and Guy David 2009, Kolstad 2013). It is possible that urologists who were at the center of the referral network cared more about their reputations, and therefore adopted active surveillance earlier than urologists who were at the periphery of the referral network. In the evaluation models, I controlled the practice styles of other physicians in the referral network in the estimation model. Urologists' practice styles were measured by Kullback Leibler Distance (KL Distance) of specific kinds of treatments. In this way, I estimate the effect of physicians' network position without the influence of the practice style of their peers.

Therefore, I hypothesize that the urologists who were at the center of the referral network receive more information about conservative treatment, and therefore will be more likely to use the conservative treatment.

2.2 Data and Methods

2.2.1 Data and Patient Cohort for Treatment Prediction

I identified patients with localized prostate cancer using the Surveillance, Epidemiology, and End Results Program (SEER)-Medicare database. SEER-Medicare is a population-based database containing Medicare claims for cancer patients residing within one of the 18 SEER registry-regions, containing approximate 34.6% of the U.S population (NIH 2018a).

I identified 704,751 men newly diagnosed with prostate cancer between January 1st 2001 and December 31st 2015. I excluded patients whose diagnosis reporting source was hospice/nursing home, autopsy report, or death certificate, as well as patients whose diagnosis date was after the date of death (n=6,665), and patients who were younger than 66 years old at diagnosis (n=243,222).

I excluded patients who did not have continuous fee for service Medicare Part A and Part B coverage after diagnosis, and who enrolled in Medicare Advantage 12 months before diagnosis and who enrolled in Medicare Advantage 12 months after diagnosis or dead within 12 months of diagnosis, whichever came first (n=178,262). I further excluded patients whose cancer was not “localized/regional” defined by the “SEER Historic Stage A” variable (NIH 2018c) (n=31,986). I also excluded patients with a cancer grade other than level I, II or III (n= 8,083) (NIH 2018b). My total patients’ cohort included 236,533 men diagnosed as localized prostate cancer between 2001 and 2015, or 179,257 men diagnosed as localized prostate cancer between 2004 and 2015. Patients’ Race/ethnicity was categorized as non-Hispanic White, non-Hispanic Black, and Other. I calculated patients’ Klabunde comorbidity index (Klabunde et al. 2000) using Medicare claims in the window of 12 months before the diagnosis month. I used the scoring method designed by Roux et al.(Roux et al. 2001) as a proxy for patients’ socioeconomic status at zip-code level.

2.2.2 Patients’ Probabilities of Undertaking Different Treatments

I used the method from Liu et al. (Liu et al. 2020) to identify the active treatment methods and active surveillance (including none treatment) for patients. I categorized treatments into four large groups: prostatectomy, IMRT, other treatment, and active surveillance and none treatment. We fit multinomial logistic regression models (Formula 1) to estimate the probabilities of patients diagnosed between 2004 and 2015 (n= 179,257) to undertake one of the three groups of treatment (Other treatment is the reference group). In this way, we consolidated important patients’ clinical indicators, demographics, social economic factors, and region and year of diagnosis into a probability for undertaking one of the four groups of treatment. This method is similar with the approach used by Currie et al. (Currie, MacLeod, and Van Parys 2016).

Formula 1:

$$ln\frac{Pr(Y_{ijt}=k)}{Pr(Y_{ijt}=3)} = \beta_0 + \beta_2\boldsymbol{X_i} + \beta_5 T_i + \epsilon_{ijt}$$

where $k = 1, 2, 4$.

For patients i treated by urologist j in period t, denote the treatment procedure by Y_{ijt}.

$$Y_{ijt} = \begin{cases} 1, & \text{if patient received surgery;} \\ 2, & \text{IMRT;} \\ 3, & \text{Other;} \\ 4, & \text{AS and None Treatments.} \end{cases}$$

Where X i is the patients’ demographic and clinical characteristics listed in Table 1, and T is the year fixed effects.

The accuracy rate of the prediction model is 61%. Table 1 is the Summary Statistics of Patients' Characteristics by Treatment Options from the treatment prediction model (Formula 1). Based on the four probabilities, we further calculated an entropy score for each patient by Formula 2. The entropy score summarized the distribution of probabilities of different treatment options, and represented how likely this patient may be treated by diversified treatment methods. Specifically, the more equally distributed the treatment probabilities (e.g., treatment probabilities of all four possible treatments are equal to 0.25) the higher the entropy score is.

$$\text{Formula 2: Entropy}_{i} = -\sum \text{Probility}(t) * \log(\text{Probability }(t))$$

Where Probability (t) is the probability of undertaking each of the four treatments for patient i. The four treatments are prostatectomy, IMRT, others, and AS and None Treatment.

Figure 1 shows the trend of patients' average entropy scores by two groups: the treatment prediction model correctly predicts the actual treatment and not. The higher the entropy score is, and the less likely that the model makes a correct prediction of the treatment method. For the patients with incorrect prediction of treatment, their average entropy score remains flat since 2006, suggesting that their probabilities of undertaking each of the treatments remain similar overtime. For the patients with correct prediction of treatment, the average entropy scores were decreasing from 2005, suggesting that different treatments were gradually targeting patients with different characteristics.

Table 2 summarizes the accuracy prediction rate for different treatment options by year diagnosis. The accuracy prediction rate for prostatectomy remained stable over time, suggesting that urologists were consistent for which groups of patients should be undertaking prostatectomy. The accuracy for IMRT and AS were increasing over time, suggesting that urologists' decision for IMRT and AS usage gradually had become consistent.

Figure 2 shows the patients' average entropy scores by different treatment options over year of diagnosis. The patients undertaking IMRT had the highest entropy score, meaning that they had the most equally distributed treatment probabilities. The patients undertaking AS and None Treatment had the second highest entropy score, and the average entropy score was decreasing over time. This observation is consistent with our hypothesis that a diversified group of patients use costly radiation therapy, e.g., IMRT, and conservative treatment, e.g., active surveillance.

2.2.3 Urologist Cohort and Analysis Sample

I used the first urologist who billed the patient in SEER's Carrier Claims dataset 180 days before diagnosis date as his treatment "decision making" urologist. I also excluded patients whose decision-making urologists' national provider identification (NPI) number or unique provider identification number (UPIN) was missing (n= 21,635). To avoid the influence of urologists who perform few procedures, I restricted our sample to urologists who had more than 10 localized prostate cancer patients all the three periods (n=61,562): 2004-2007 (period 1), 2008-2011 (period 2) and 2012-2015 (period 3). I further excluded the urologists whose teaching affiliation is unknown (n=5,550) and urologists missing other variables (n=2,702) in our analysis. In our final analysis dataset, there are a total of 87,808 patients diagnosed between 2004 and 2015, and treated by 863 urologists. Table 3 summarizes the Analysis Sample Selection Process.

2.2.4 Urologists' Practice Style

Patients' demographics (because of screening policy changes) and popular treatment patterns (because of clinical guideline and new technology) may had changed for urologists over time. I need to combine the patients' specific cancer risk factors and the overall treatment distribution, in order to measure a urologist's styles. I used Kullback Leibler Distance (KL Distance) (Formula 3) to achieve this goal. Kullback Leibler Distance (KL Distance) summarized the differences between the expected probabilities distributions and the observed probabilities distribution (Kullback and Leibler 1951). The KL Distance had been used in the fields of hypertension prediction (Clim, Zota, and TinicĂ 2018), medical imagine recognition (Xue et al. 2020), personal sleeping pattern (Phan et al. 2020), cell segmentation of biomedical reearch (Scherr et al. 2020), and artificial intelligence (Fekri Ershad 2019, Harb and Chen 2005, Xiao, Zhao, and Wang 2018). In my analysis, each patient had four predicted probabilities of undertaking four different categories of treatments based on the market average prediction, and the urologist chose one treatment for the patient. I assumed that the predicted probabilities of the four categories of treatments were the "true" probabilities distribution, and compare this "true" probabilities distribution with urologists' choice. For example, a urologist who treated patients who were suitable for prostatectomy (had a higher probability of prostatectomy) and eventually chose prostatectomy would have a lower prostatectomy KL Distance, compared to an urologist who chose active surveillance for the same group of patients.

There were few steps to calculate the KL Distance scores of each urologist for different kinds of treatment. First, I calculated the KL Distance for each patient and for each of the four large treatment methods (Prostatectomy, IMRT, Others, and Active Surveillance and None Treatment) using his predicted treatment probabilities (from Formula 1) distribution, which consolidated his major clinical and demographic characteristics and overall treatment trends. Second, I aggregated this KL Distance by each urologist for each of the four large treatment categories for each period (or each year depending on the length of evaluation time). Each urology has four KL Distance scores, (1) Prostatectomy, (2) IMRT, (3) Other Treatment, and (4) Active Surveillance and None Treatment (AS) for each period. For example, the Prostatectomy KL Distance for Urologist A represents that if Urologist A chose to use prostatectomy as the treatment approach for her patients in this period, how much difference her choice is from the prediction of the entire market.

$$\text{Formula 3: } KL_T = \sum \text{Probability}_T * \log(\text{Probability}_T/\text{Probability}_{T,i})$$

Where T is the treatment options, including Prostatectomy, IMRT, Others and Active Surveillance and None Treatment. $\text{Probability}_{T,i}$ is the probability of each treatment for patient i calculated by the multinomial logistic regression models Formula 1. Probability_T is the default probability of the treatment the urologist believed that the patient should undertake if this treatment was selected as the final treatment by this urologist. I set $\text{Probability}_T = 0.9$ if treatment T is the final selection. $\text{Probability}_{\neq T} = 0.03$ for the other three alternatives. The value of "0.9" and "0.03" are my arbitrary choice and may be adjusted for sensitivity checks. By Formula 3, I calculated the KL Distance for the 4 treatment categories separately, e.g., KL Distance of Prostatectomy, KL Distance of IMRT, KL Distance of Others, and KL Distance of Active Surveillance.

Figure 3 shows the average KL Distance Distances of prostatectomy, IMRT, and AS for the 863 urologists in our analysis sample over time. Figure 3 shows that the prostatectomy KL Distance remained stable and low since 2007, which suggests that the urologists were consistent with what kinds of patients should undertake prostatectomy. The KL Distance for IMRT and AS were high and were decreasing since 2004. This trend suggests that there existed discrepancies for what kinds of patients should be using IMRT or AS, however the levels of discrepancies are decreasing. Table 4 summarizes the correlation between KL Scores and treatment usage percentage, the correlation between KL Scores and patients' aggregated entropy score at urologists' level, and the correlation between KL Scores and patients' volume. Table 5 summarizes the correlations among different KL Scores, and Table 6 summarizes the correlations among different usage percentages of different treatments.

2.2.5 Urologists' Referral Network

There were several steps to establish physicians' referral network. I first established a connection between a urologist and a patients' main primary care doctor (Pham et al. 2007) based on an existing algorithm (Barnett, Landon, O'Malley, et al. 2011). I defined that two urologists who shared the same referral network if they were connected through a patient's main primary care doctor. Figure 4 illustrate the network graph for a sample of 200 randomly selected urologists of all the urologists' sample (rather than the 863 urologists with more than 10 patients for each period). Because we randomly selected 200 urologists, some of the urologists don't have any connections with each other. We then calculated the closeness centrality of a urologist in her referral network as a proxy for urologists' network position. The closeness centrality measures how well a urologist is connected to other urologists in her referral network (Jackson, Rogers, and Zenou 2017). The "closeness centrality" score reflects the number of paths of a urologist to all other urologists in his/her referral network. The higher the "closeness centrality" score, the lowest number of paths this urologist needs to reach other urologists in the network. Theoretically, a urologist with the highest closeness centrality score were more likely to receive information from the referral network. Figure 5 shows the distribution of urologists' closeness centrality trends for period 1 (2004-2007), period 2 (2008-2011), and period 3 (2012-2015). In the analysis, we categorized a urologists' closeness centrality of each period into high, medium, and low by tercile. Table 7 is the summary statistics of our analysis sample by different urologists' network groups.

2.3 Model

2.3.1 A Simple Theoretical Model

We defined urologists i and urologist j in the same referral network in period t, and Wi,j denotes the number of information channels connected between the two urologists in period t. Dj,t denotes the possible information exchange, where

$$D_{ijt} = \sum W_{i,j,t} + \sum W_{j,i,t}$$

$$D_{jt} = \sum D_{i,j,t}, \quad j \neq i$$

We denote that B_{it}^{AS} is the positive belief of active surveillance usage for localized prostate cancer patients by urologist i and M_{jt}^{AS} is the message urologist j may receive from her referral network established by primary care doctors.

$$M_{jt}^{AS} = \sum_{i \neq j} B_{it}^{AS} + U_{it}^{AS}, \quad U_{it}^{AS} \sim \mathrm{N}(0, \sigma^2)$$

Urologist j's positive belief of active surveillance in period t, $B_{j,t}^{AS}$, equals to her belief from the previous period plus the probability that other urologists' net positive belief (because active surveillance has become increasingly popular, I assume that most of the urologists would have a net positive belief, especially after 2012 when the NCCN passed the treatment guideline with active surveillance) will be transmitted to her through the network:

$$B_{j,t}^{AS} = B_{j,t-1}^{AS} + GM_{jt}^{AS} + \epsilon.$$

$$G = \begin{cases} 1, & Pr = 1 - q^{D_{jt}}; \\ 0, & Pr = q^{D_{jt}}. \end{cases}$$

Where q (less than 1) is the probability that the positive belief was not transmitted through the network by primary care doctors. With some simple mathematical derivation, we can obtain that,

$$\ln \mathsf{E}(B_{j,t}^{AS} - B_{j,t-1}^{AS}) \propto -\ln \mathsf{E}(M_{jt}^{AS}) - D_{jt} \ln q$$

which shows the larger the possible information exchange with other urologists (measured by closeness centrality in our empirical model), $D_{j,t}$, the more likely that an urologist will increase her positive belief of active surveillance usage for localized prostate cancer between period t-1 and period t.

2.3.2 Econometric Model

The main purpose of this study was to evaluate the impact of urologists' referral network position on her adoption of active surveillance. I adopted a probit regression model (Formula 4 use Active Surveillance as an example) to estimate patient i's probability of undergoing each treatment (e.g., active surveillance [AS], Prostatectomy [surgery], IMRT) treated by urologist j in period t.

Formula 4:

$$Pr(\Gamma_{ijt} = 1) = \Phi(\beta_0 + \beta_1 \boldsymbol{CloGrp}_{jt} + \beta_2 \boldsymbol{ProbAS}_i + \beta_3 \boldsymbol{Entro}_i + \beta_4 PeerSty_j + \beta_5 Phy_i + \beta_5 HHI_i + \epsilon_{ijt}) \quad \Gamma_{ijt} = \begin{cases} 1, & \text{if patient received AS;} \\ 0, & \text{other treatment.} \end{cases}$$

Where, CloGrp represents urologist j's network group (high, medium and low) in period t. ProbAS represents patient i's probability of undertaking active surveillance, and Entro represents how likely that patient i will be treated by different treatment options with equal probabilities. ProbAS and Entro are estimated from Section 2.2.2 by summarizing patients' characteristics and the treatment patterns of the years of diagnosis and of the region. PeerSty is the aggregated practice style (e.g., Active Surveillance KL Distance for evaluating the probability of Active surveillance) for all the urologists in urology j's referral network in period t. The reason to include PeerSty is to control for the peer effects of the referral network and obtain the effects of the network position. Phy is the urologists j's characteristics in period t (including whether urologist worked at solo practice, IMRT self-referral status, patient's volume, and whether urologist worked at teaching institute). HHI is the Herfindahl-Hirschman Index (Rhoades 1993) of the health service area where urologist j practice in period t. I evaluated formula 4 by three periods: 2004-2015, 2004-2011, and 2012-2015. Subgroups include urologists affiliated with teaching institute, solo practice, and IMRT self-referral facilities. I performed 100 bootstrap replications for each model to derive the confidence intervals.

2.4 Preliminary Results

2.4.1 Urologists' Network Group and Patients' Characteristics

Table 7 shows the summary statistics of urologists' characteristics and patients' characteristics for urologists of different network group (low, medium and high). Table 7 shows that the urologists of the three network groups have similar usage percentage of active surveillance, and patients' characteristics (e.g., age, race, comorbidity, and entropy score), and similar KL Distance scores for all three treatment types. The similar patients' characteristics for urologists of different network groups suggests that urologists were not selecting patients because of their network position. Urologists of higher network group, e.g., urologists' closeness centrality scores were the top 33 percentile, are more likely to practice at a health service area with higher levels of competitions. This is reasonable because the service area with higher levels of competition had more urologists, therefore the urologists tended to have more network connections.

2.4.2 Urologists' Network Group's Impact on Adoption of Active Surveillance

Table 8 shows patients' probabilities and the 95% confidence interval of undertaking active surveillance by network groups, and in different periods, evaluated by Formula (4). Supplementary 1 summarized the Coefficients, standard errors, and 95% confidence interval of the result evaluated by formula (4) when it ran once. Urologists of high network group had a higher probability of using active surveillance than urologists of low network group, and the effect was more obvious for the period of 2012-2015, after NCCN introduced the clinical guideline of active surveillance usage. Figure 6 summarized probabilities of undertaking prostatectomy, IMRT, active surveillance by urologists of different network groups and different periods using boxplot. From Table 8, we can see that between 2004 and 2015, the patients treated by urologists who were at higher network group had higher probabilities of undertaking active surveillance. The effect was more obvious for the period between 2012-2015 after NCCN introduced active surveillance as a treatment in guideline. Figure 6 shows that the network effect was different for prostatectomy and IMRT. The probabilities of undertaking prostatectomy was higher for patients treated by urologists in higher network group before 2012. However, there was no significant differences for the probabilities of undertaking prostatectomy between 2012 and 2015. Patients treated by urologists who were at the peripheral of referral network have highest probabilities of undertaking IMRT.

2.5 Subgroup and Sensitivity Analysis

2.5.1 Teaching status, solo-practice, IMRT self-referral subgroups

One of the major concerns was that urologists' teaching status, practice location (e.g., whether urologists practice at solo practice), and whether urologists practice at an IMRT self-referral clinic determined their referral network position, therefor are endogenous to the results. I conducted few tests.

I first used logistic regression models (formula 5) to evaluate the differences of treatment probabilities between two subgroups (e.g., teaching vs non-teaching groups, multi-urologists practice vs solo urologist practice, and IMRT self-referral vs None IMRT self-referral) in the periods of 2004-2011 and period of 2012-2015. Figure 7 Panel A summarizes the probabilities differences for active surveillance, and Figure 7 Panel B summarizes the probabilities differences for IMRT, and Figure 7 Panel C summarizes probabilities differences for prostatectomy.

Formula 5:

$$ln(\frac{Pr(t)}{1-Pr(t)}) = \beta_0 + \beta_1 \boldsymbol{CloGrp}_{jt} + \beta_2 \boldsymbol{ProbAS}_i + \beta_3 \boldsymbol{Entro}_i + \beta_4 PeerSty_j + \beta_5 Phy_i + \beta_5 HHI_i + \epsilon_{ijt})$$

Where, t is treatment method. I fitted three models for three treatments: AS, IMRT, and Prostatectomy respectively for the two periods (2004-2011 and 2012-2015). CloGrp represents urologist j's network group (high, medium and low) in period t. ProbAS represents patient i 's probability of undertaking active surveillance, and Entro represents how likely that patient i will be treated by different treatment options with equal probabilities. ProbAS and Entro are estimated from Section 2.2.2 by summarizing patients' characteristics and the treatment patterns of the years of diagnosis and of the region. PeerSty is the aggregated practice style (e.g., Prostatectomy KL Distance for evaluating the probability of prostatectomy) for all the urologists in urology j's referral network in period t. Phy is the urologists j's characteristics in period t. The urologists' characteristics we are interested in include urologists' teaching affiliation, whether urologist worked at solo practice, IMRT self-referral status. These three physician characteristics are dummy variables. Other physician characteristics include patient's volume. HHI is the Herfindahl-Hirschman Index of the health service area where urologist j practice in period t.

Figure 7 Panel A shows that the probability differences of using active surveillance between teaching and none-teaching hospitals decreased slightly from 2004-2011 to 2012-2015. This observation suggests that the urologists affiliated none teaching hospitals adopted the usage of active surveillance later than urologists affiliated with teaching facilities, but the differences between the teaching and none teaching urologists gradually disappeared. Urologists practicing at multi-practice and urologists practicing at practices that do not own IMRT equipment were consistently more likely to use active surveillance than their counterparts. For the probability differences for IMRT usage, the results were consistent with other anecdote evidence and other research results. For example, self-referral urologists were more likely to use IMRT than their counterparts. In the period of 2004-2011, urologists affiliated with teaching institutes were more likely to use prostatectomy than urologists not affiliated with teaching institutes.

I used T-test to evaluate whether the urologists of two groups (e.g., teaching vs non-teaching, solo vs multi practice, and IMRT self-referral vs None IMRT self-referral) had different network scores. Table 9 shows the t test results. Teaching group and the IMRT self-referral group had higher referral network closeness scores than their counter part groups. The referral network closeness scores were higher for urologists who practiced at multi-urologists' clinic than urologists who practiced at a solo clinic at 0.05 significance level. The T-test results showed that urologists affiliated with teaching facilities, multi-urologists' practice, and IMRT self-referral institutes had higher network scores. We had included these three factors in the model (formula 4) to control for the impacts of these factors. The direction of coefficients for whether urologists practiced at solo or multi- urologists groups, and whether urologists practiced at IMRT self-referral institutes were opposite from the direction of coefficients for network position's impacts on active surveillance usage. For example, IMRT self-referral was associated with lower usage of active surveillance, IMRT self-referral group was associated with higher network, and higher network was associated with higher usage of active surveillance. Therefore, the impacts of multi-urologists status and IMRT self-referral status on active surveillance usage biased our results towards 0. However, the impact of teaching status biased our results upwards.

I then used logistic regression models (Formula 6) to evaluate the probabilities of active surveillance usage by urologists affiliated with teaching institutes, and for urologists not affiliated with teaching institutes. The goal was to identify whether the network group effects were different among urologists with different teaching statuses. The results were reported in Figure 8. From Figure 8, we can see that the patterns of active surveillance usage differences between high and low network groups were similar for urologists affiliated with teaching institutes and for urologists not affiliated teaching institutes. In the period of 2004-2011, the active surveillance usage probability differences between high and low network group was not different from 0 for urologists of both teaching affiliated urologists and not teaching affiliated at the significance level of 0.05. For example, for urologists affiliated with teaching institutes, patients treated by high-network group urologists had a 7.25 percentage points higher probability of undertaking active surveillance (P=0.105) than patients treated by low-network group urologists. In the period of 2012-2015, the urologists with a higher network score had higher active surveillance usage probability than urologists with a low network score for both groups. For example, for urologists affiliated with teaching institutes, patients treated by high-network group urologists had a 24.48 percentage points higher probability of undertaking active surveillance (P=0.001) than patients treated by low-network group urologists. For urologists not affiliated with teaching institutes, patients treated by high-network group urologists had a 20.80 percentage points higher probability of undertaking active surveillance (P=0.012) than patients treated by low-network group urologists. This result suggests that regardless of urologists' teaching affiliation, the urologists with higher network score adopted the active surveillance usage faster than urologists with lower network score after the guideline changes.

Formula 6:

$$ln(\frac{Pr(AS)}{1-Pr(AS)}) = \beta_0 + \beta_1 \boldsymbol{CloGrp}_j + \beta_2 \boldsymbol{ProbAS}_i + \beta_3 \boldsymbol{Entro}_i + \beta_4 PeerSty_j + \beta_5 Phy_i + \beta_5 HHI_i + \epsilon_{ij}$$

Where, CloGrp represents urologist j's network group (high and low). ProbAS represents patient i 's probability of undertaking active surveillance, and Entro represents how likely that patient i will be treated by different treatment options with equal probabilities. ProbAS and Entro are estimated from Section 2.2.2 by summarizing patients' characteristics and the treatment patterns of the years of diagnosis and of the region. PeerSty is the aggregated practice style (e.g., Prostatectomy KL Distance for evaluating the probability of prostatectomy) for all the urologists in urology j's referral network in period t. Phy is the urologists j's characteristics (including whether urologist worked at solo practice, IMRT self-referral status, and patient's volume). HHI is the Herfindahl-Hirschman Index of the health service area where urologist j practice. I fitted four separate models using Formula 6: urologists associated with teaching institutes in the period of 2004-2011, urologists affiliated with teaching institutes in the period of 2012-2015, urologists not affiliated with teaching institutes in the period of 2004-2011, and urologists not affiliated with teaching institutes in the period of 2012-2015. The results were reported in Figure 8 and described above.

2.6 Limitations and Future Work

In the near future, I hope to conduct additional sensitivity analysis. For example, for the treatment probability prediction model and urologists' practice style calculation, I will group treatments by different approaches with more details, e.g., separate active surveillance and none-treatment, and use more detailed radiation therapy treatments categories. I may also use smaller areas, e.g., health service area, rather than SEER region, to adjust for local impact. Several major areas may need attention when evaluating my results.

2.6.1 Urologists Types and Adoption of Active Surveillance

We group urologists' cancer patients into two periods (2004-2011 and 2012-2015) in my main analysis, because of the limitation of number of cancer cases. We currently use the plural claims to identify an urologists' main practice location, academic affiliation, and other characteristics for the period. Long time span in one period may create measurement errors and does not allow us to accurately identify the gradual diffusion process of active surveillance treatment year by year.

My analysis also showed few interesting phenomena. Urologists who were at the center of referral network had highest usage of active surveillance, and at the same time the lowest usage of IMRT (Figure 6). The usage differences between referral network groups for prostatectomy and AS were similar between 2004-2011, but not 2012-2015 (Figure 6). This result suggested that between 2012 and 2015, when active surveillance usage became increasingly popular, urologists who used prostatectomy as their main treatment approach switched to AS more than urologists who used IMRT as their main treatment approach.

2.6.2 Accuracy of Referral Network

We used patients from a single payer (Medicare) to measure urologists' referral network. Though there was a high correlation between the number of Medicare patients and the number of private insured patients shared by physicians (Trogdon et al. 2019), it was still possible that urologists' referral network was different based on all her patients compared with Medicare beneficiaries only.

We may also test other network measures that reflecting urologists' position in a referral network. I may also compare the impacts of urologists' referral work and urologists' network established by shared patients or shared practice.

At a macro level, the structure of a health service area's network has an impact on information accumulation and diffusion (Alatas et al. 2016), therefore influencing the adoption and the variation of usage of evidence based practice. In addition, the referral network established by primary care doctors may be associated with specific patients' demographic features (Landon et al. 2021), therefore influencing treatment choices. Secondly, I was planning to measure the influence of primary care doctors (for example, the percentage of initial prostate cancer screening test ordered by primary care doctor) within a referral network or within a health service area. I want to use the influence of primary care doctor as an instrument to evaluate the impact of referral network structure on treatments diffusion.

2.7 Summary

Physicians often learn new treatments from their peers. Physicians' network positions is associated with the information they receive (Tasselli 2014, Jackson, Rogers, and Zenou 2017, Mascia, Cicchetti, and Damiani 2013, Fattore et al. 2009, Mascia and Cicchetti 2011, Pollack et al. 2012, Landon et al. 2012, Sykes, Venkatesh, and Rai 2011, Barnett, Landon, O'Malley, et al. 2011, Donohue et al. 2018). Active surveillance for localized prostate cancer is gradually adopted by urologists over time when clinical evidence is accumulating. Our work extends current physician network analysis by using patients' primary care doctors as connections to establish specialists' referral network and their information transmission channels. Though there is no firm conclusion whether investing in primary care doctors will save the healthcare cost of the US (Song and Gondi 2019), our results suggest that primary care doctors may serve as an "information hub" to disseminate conservative treatment approach within specialists' referral network. In the era of personalized medicine, patients' primary care doctors may play an increasing role in patients' treatment decision making (Jang et al. 2010, Klabunde et al. 2009), especially for early stage cancer treatment and management decisions (Radhakrishnan et al. 2021).

3 Physician Peer Influence on Active Surveillance and Other Treatment Choices

3.1 Background

Peers had impact on physicians' choice of treatment. Most of the current studies of peer effects were investigating drug diffusion (Agha and Molitor 2018, Nair, Manchanda, and Bhatia 2010, Bhatia and Wang 2011, Yang, Lien, and Chou 2014, Coleman, Katz, and Menzel 1957, Winick 1961, Iyengar, Van den Bulte, and Valente 2011), and active treatments (Molitor 2018, Sacarny, Olenski, and Barnett 2019). Less is known about physicians' peer effects on conservative disease management strategies.

Peers' impacts on adoption of conservative treatment methods, such as active surveillance for prostate cancer, may be different from the peers' impact on the adoption of active treatments. First, active surveillance is not a new technology for localized prostate cancer treatment. Urologists may not need additional training or technologies to practice active surveillance. Capacity and productivity of the institute (Chandra and Staiger 2007, Chandra et al. 2016) also have limited impact on the usage of active surveillance. Second, external factors, e.g., direct marketing intervention (Van den Bulte and Lilien 2001) have limited influence on the usage of active surveillance. Third, it seems not plausible that physicians' treatment preference for active surveillance is a factor for choice of practice location. When a physician chose practice location, he/she may select a practice with similar practice styles as he/she current had. It is also possible that a physician chose practice location because of a new technology. Therefore, when evaluating peers' impact on treatment choices, the results may be biased by physicians' personal practice location preference. It seems unlikely that physicians choose a practice location because she/he wants to practice conservative treatment, e.g., active surveillance for localized prostate cancer. Therefore using conservative treatment to evaluate peers' influence may not be influenced by the same bias as active treatment has.

Given the differences between active treatments and conservative treatment listed above, I wanted to estimate the peer influence on urologists' choice of active surveillance, and compare the peer influence of active surveillance to the peer influence of other active treatment, e.g., proctectomy and IMRT.

3.2 Urologist Practice Styles and Cohort

3.2.1 Urologists' Co-workers' Practice Styles

We used two approaches to measure urologists' co-workers' practice styles. The first approach was the percentages of treatment options used. The percentages of treatments were not adjusted by patients' characteristics and time trends factors. I also used a second approach to measure urologists' practice style: the KL Distance of urologists for different kinds of treatment. The KL Distance scores incorporated the treatment trends of the year, and patients' demographics and disease characteristics. The KL Distance scores represented the similarity between a urologist' choice of a specific treatment and the market average. For example, a high average Active Surveillance KL Distance score of a urologist means that when this urologist selected patients for active surveillance treatment, her selection criteria were very different from the market average. Please see more details at Chapter 2 Section 2.2.4 for Urologist's KL Distance scores.

3.2.2 Urologist's Cohort

In order to evaluate the impact of peers, I used urologists who changed practices between 2005 and 2015 as the identification strategy. This concept was similar to Molitor 2018 (Molitor 2018). There were a few steps to identify urologists who changed practices, and to identify their coworkers before and after the move. First, I identified urologists' main practice location from SEER-Medicare using the plurality of office visits claims by tax identification number between 2002 and 2015 (n=10,557). Second, I identified the urologists who moved from one practice to another practice if her main practice location changed between two consecutive years in the period of 2005 to 2015, and the urologists whose tax identification number still existed after she billed new practices (n=1,628). I eliminated the urologists whose tax identification number no long existed after she/he billed a new practice, because I assume that if the tax identification number no longer existed, this urologists' practice was bought or merged with other practice. Because I want to evaluate the impact of peers, if the entire practice was bought or merged into a new practice, the urologists may have the same peers before and after the move. For the urologists that changed practice more than once between 2004 and 2015, we currently used the first time they change practice. In addition, I used a subgroup of urologists who had high volume of patients. Specifically, I restricted the urologists who had more than 5 patients before and after the move (n=176). Third, I identified the patients treated by the coworkers of each of the 176 urologists during the time that this urologist worked at this practice. I had a total of 10,883 patients treated by 176 urologists in the sample. I aggregated each urologist's co-workers' practice style measures, including their percentages of each kind of treatment, and KL Distance scores during the period when this urologist practiced at this location. The KL Distance scores included four large categories of treatment: prostatectomy, IMRT, Other treatments, and Active Surveillance and None Treatment. To obtain more accurate estimations for the impacts of peers' practice styles, in each of the model below I further restricted the sample size to urologists whose coworkers also had more than 5 patients in the associated periods. For example, for Formula 1 below, I used the urologists whose previous coworkers and current coworkers had more than 5 patients during the period after the move.

3.2.3 Hypotheses and Models

My first hypothesis (Hypothesis 1) was: after a urologist moved to a new practice, her new coworkers' practice styles (Coworker after move) had a larger impact than her pervious coworkers' practice styles (Coworker before move). To evaluate Hypothesis 1, I used a logistic regression to compare the impacts of new practice's coworkers and the impacts of previous practice's coworkers on treatment choice after urologists' move (Formula 1). I compared the coefficients of "Coworker before move"(β1) and "Coworker after move" (β2), and repeated 5,000 times to obtain confidence intervals. I reported results of using percentage in Figure 4 and the results of using KL Distance in Figure 5.

Formula 1:

$$ln(\frac{Pr(t)}{1-Pr(t)}) = \beta_0 + \beta_1 \boldsymbol{Coworker\ before\ move}_{j,s} + \beta_2 \boldsymbol{Coworker\ after\ move}_{j,s} + \beta_3 Prob_{i,t} + \beta_4 Entro_i + \beta_5 year + \epsilon_i$$

Where t treatments options, I evaluated treatment of IMRT and Active Surveillance separately; s represents practice styles of urologists. I used two practice styles and evaluated the impacts of these two styles separately: percentage of treatment usage and KL Distance. Prob represents the probability of treatment t for patient i, and this probability incorporated patients' demographic and clinical characteristics, year of diagnosis, and region. Entro is the patient's entropy score of undertaking different treatments, representing how likely the patient will be treated by equal probabilities of the four large categories of treatment options. Prob and Entro were evaluated by the formulas from Chapter 2 Section 2.2.2 Patients' Probabilities of Undertaking Different Treatments.

The second hypothesis (Hypothesis 2) was: the peers' practice styles had larger impact when the urologist and the peers were coworkers than when this urologist and the peers were not coworkers. The peers were urologists' coworkers who may had worked with the urologists either before or after the moving to other practices. To evaluate Hypothesis 2, I used a conditional logistic regression using each urologist as a "pair", and evaluated coworkers' impact when this urologist was working with the coworkers at the same practice compared to the same urologist when she/he was not working with the coworkers in this practice (Formula 2). Conditional logistic regression is a technique for matched case-control study (Lipsitz, Parzen, and Ewell 1998). In my study design, the conditional logistic regression incorporated the unobserved urology level's personal fixed effects. I reported odds ratio of the results in Table 3. For both Hypothesis 1 and Hypothesis 2, I evaluated the treatments choice for IMRT, and Active Surveillance and None Treatment separately to compare the peers' impact on these two kinds of treatments.

Formula 2:

$$ln(\frac{Pr(t)}{1-Pr(t)}) = \alpha_j + \beta_1 \boldsymbol{Coworker\ before\ move}_{j,s} \# prepost_{i,j} + \beta_2 \boldsymbol{Coworker\ before\ move}_{j,s} \# prepost_{i,j} + \beta_3 Prob_{i,t} + \beta_4 Entro_i + \beta_5 Year + \epsilon_i$$

Where α_j is the individual urologist fixed effects, prepost is an indicator whether patient i was treated by urologist j before or after the move. The other independent and dependent variables are the same as Formula 1.

Third, I wanted to evaluate whether a urologist move to a new practice because of specific practice styles or technologies. Specifically, in the period before moving to a new practice, if the practice styles of coworkers after move had larger impact on urologists' usage of a treatment than the practice styles of coworkers before the move had, this result suggested that the urologist moved to the new practice due to the similarities with the practice styles of the coworkers after the move. Urologists may choose a practice location because usage of technology, e.g., IMRT or prostatectomy, but it was unlikely that urologists choose a practice location because of the usage of active surveillance. Therefore, my third Hypothesis (Hypothesis 3) was: in the period before moving to a new practice, the practice styles for active treatments of coworkers after the move had an impact on treatment choices; however, the practice styles for active surveillance of coworkers after the move did not have the same impact. To evaluate Hypothesis 3, I used a logistic regression model (Formula 1) to identify the impact of a urologist's coworkers before move and the coworkers after move on her usage of three different treatments in the period before moving. For Hypothesis 3, I estimated Formula 1 using the patients treated by urologists before the move. I compared the coefficients of "Coworker before move" ($\beta 1$) and "Coworker after move" ($\beta 2$), and I repeated 5,000 times to obtain confidence intervals. I reported the results of percentage in Figure 6 and the results of KL distance in Figure 7.

Lastly, I wanted to test whether there existed division of labor among urologists within a practice. If there existed a division of labor within practice before the move or after the move, the selection of treatment may be influenced by the division of labor rather by the peer impact. I conducted a paired T-test to compare patients' average probabilities of different treatments and patients' average entropy scores between urologists who moved practice and his/her coworkers before the move in the period before moving, and compare the same measures between urologists and his/her coworkers after the move in the period after moving. If there existed significant differences between the urologists and their coworkers for patients' treatment probabilities, the results suggested a division of labor. The p-value of Ttest comparison results were reported in Table 4.

3.3 Preliminary Results

3.3.1 Urologists' Characteristics Before and After Move

Figure 1 reports the distribution of the year that urologists changed practice. Figure 2 reports the number of years urologists practice before and after the move. The average number of years that urologists practiced before moving was 6.19 and the average number of years that urologists practiced after moving was 5.02. The average number of years after move was shorter than the average number of years before move may be because of the limited time frame of our dataset.

Figure 3 shows the comparison of patients' volumes in the period before and in the period after the move for the three groups of urologists: the urologists moved the practice (our targeted urologists), his/her coworkers before moving, and his/her coworkers after moving. Our targeted urologists' average patients' volume decreased from 35 to 27 after the move. Average patients' volume of urologists' coworkers before moving decreased from 164 to 75. Average patients' volume of urologists' peers after moving increased from 93 to 193. The patients' volume difference between our targeted urologists and coworkers before moving in the period before moving was 129. The patients' volume difference between our targeted urologists and coworkers after moving in the period after moving was 166. The patients' volume of our targeted urologists did not change much before and after the move. However, the patients' volume of coworkers before moving had decreased and the patients' volume of peers after moving had increased. This suggested that the size of the practice reduced after one or more urologists moved to other practice, and the size of the practice expanded after one or more urologists joined the practice.

I also compared patients' demographics for the urologists before and after moving to a new facility. Table 1 summarizes the patients' characteristics, e.g., age and race/ethnicity categories, comorbidities, and probabilities of different treatments. The patients' characteristics are consistent with the general trends. For example, more patients within the age group 66-74 and more patients with a Gleason score of 7 were diagnosed as localized prostate cancer after a urologist changed practice. This was because the screening guideline changes during the later period of our sample. Urologists' average patients' entropy scores decreased, which suggested that the probabilities of the patients undertaking different treatments became more evenly distributed after moving to a new practice. This was also consistent with the general trends of patients' average entropy score over time (Figure 1 of Chapter 1).

3.3.2 Urologists and Their Co-workers' Practice Styles

Table 2 summarizes urologists and their co-workers' practice style measures before and after the move. Higher urologist level treatment entropy scores represented that this urologist's percentages of treatment were equally distributed. Higher KL scores means that the urologists' usage of this specific treatment was different from the market average after controlling for patients' characteristics. Similar to the analysis from Chapter Two Section 2.2.4 Urologists' Practice Style, we can see from Table 2 that the percentage of usage and the KL scores may not move the same direction for a treatment. For example, for the coworkers before move, the percentage of usage of active surveillance and none treatment increased from 24.20% to 29.31%, but the average Active Surveillance KL scores decreased from 0.87 to 0.67. These results implied that the usage of active surveillance has increased and at the same time the selection criteria for patients using active surveillance had been closer to the market average.

3.3.3 Peers' Impacts on Urologists' Selection of Treatment after Moving to a New Practice

Figure 4 and Figure 5 reports the results of Formula 1. From Figure 4, we can see that after moving to a new practice, the percentage of usage for both active surveillance and IMRT of the coworkers from the new practice had a significant impact (at 95% confidence interval level) on the selection of treatment choice. Figure 5 shows that the KL scores of IMRT of coworkers from new practice had an impact of the choice of IMRT (at 95% confidence interval level), but not for the treatment choice of AS.

Table 3 reports the odds ratio of urologists' impacts as a coworker compared to the same group of urologists not as a coworker (Formula 2). For example, Urologist A moved practice, and before moving, Urologist A had a coworker Urologist B. After moving, Urologist B was not longer the coworker of Urologist A. We compared Urologist B's impact on Urologist A when Urologist B and A were coworkers to Urologist B and A were not coworkers. If we used percentage usage as practice style measurement, being a coworker before moving to a new practice has 18.36 times the impact of not being a coworker for the selection of active surveillance. For the practice style of KL scores, being a coworker before moving to a new practice has 3.78 times the impact of not being a coworker for the selection of active surveillance. The impacts of being co-workers after the move was similar to the impact of being co-workers before the move. For the impact of percentage of treatment on the selection of IMRT, coworkers had significant larger impact when being coworkers compared to not being a coworker. However, compared to not being a coworker, being a coworker did not have a significant impact for treatment choice for IMRT using KL Distance scores as the practice style measurement.

3.3.4 Urologist Move to a Practice Because of Practice Style and Division of Labor

Figure 6 and Figure 7 show the results of Formula 3. Figure 6 reports the impact of percentage of treatments on urologists' choice of different treatments from two groups of coworkers (coworkers before move and the coworkers after move) before moving to a new practice. We did not observe that the coworkers after move have a positive impact on the selection of any of the treatment choices during the period of before moving. Figure 7 shows the impact of KL Distance of treatments on urologists' choice of different treatment from two groups of coworkers (coworkers before move and the coworkers after move) before moving to a new practice. The KL Distance of prostatectomy of coworkers after move had a significant impact (at 95% confidence interval) on the selection of prostatectomy. This result suggests that urologists may select to move to a practice because of the practice style of prostatectomy by coworkers after the move.

Table 4 reported the P-value of the paired T-test, comparing the average probabilities of treatments and average patients' entropy scores between urologists who moved and his/her coworkers before the move in the period of before moving, and between urologists who moved and his/her coworkers after move in the period of after moving. There were no significant differences for the average probabilities of active treatments and average patients' entropy score between urologists who moved and their coworkers. There existed differences of patients' probabilities of undertaking active surveillance. In the period before moving, the patients' average probabilities of undertaking active surveillance for urologists who moved practice was 1 percentage point lower than the patients' probabilities of undertaking active surveillance by his/her coworkers' patients (p=0.03). In the period after moving, there were no differences for the probabilities of active surveillance between the urologists who moved and his/her coworkers.

3.4 Limitations

First, my urologist sample size was small with only 176 urologists who had moved from practice to another, and had more than 5 patients before and after the move. The small sample size made it difficult to identify impacts of peers on treatment choices. The measurement of coworkers' practice styles may not be accurate also because of the limited sample size.

Second, I used the plural of clinic visit claims as identification for a urologist move between different practices. SEER-Medicare dataset only has claims for Medicare beneficiaries. I may not be able to accurately identify a urologist's practice location and her co-workers. As discussed for the results of Figure 3, I may mis-categorized urologists whose practices were bought by other practice as urologists who moved from on practice to another.

Third, because of the limited number of patients, I categorized two periods: before urologists' move to a new practice and after urologists' move to a new practice. Average lengths before move and after move were about 5-6 years. A period of 5 years may be long for evaluating peer influence on treatment choices. A shorter period would provide more accurate estimate of peers' impact on physicians' treatment choice after physician move to a new environment.

3.5 Conclusions and Discussion

3.5.1 Comparison of Percentage Usage and KL Distance Score as Practice Style

I used two ways to reflect urologists' practice styles: the percentage of usage of a treatment and the KL Distance scores. The results from Table 3 illustrated that the two practice styles may have different impacts. For example, Table 3 showed that being a coworker had a larger impact on the usage of IMRT using percentage of treatment as a practice style measurement. However, for KL Distance scores, being a coworker did not have the same impacts for IMRT treatment. This observation implied that for active treatment, being a coworker compared to not being a coworker, the percentage usage had an impact peers, but the patients' selection criteria did not have an impact. The urologists may benchmark their coworkers for similar percentage of usage, but at the same time their patients' selection criteria may not be the same.

For increasing popular conservative treatment, e.g., active surveillance, being coworkers had similar moderately larger impacts on treatment choice for both percentage of treatment and KL

Distance, compared to not being coworkers. This implied that urologists may benchmark their coworkers for similar percentage of usage, and patients' selection criteria.

3.5.2 Impacts of Co-workers for Different Treatments

Figure 4 shows that after a urologist move to a new practice, her new coworkers' percentage of usage for IMRT and Active Surveillance had a significant impact on her choice of treatment. This observation is consistent with Molitor 2018 (Molitor 2018). These results suggested that using percentage of treatment as the practice style measure, the impacts of peers were the same for active treatment and conservative treatment methods. Figure 5 shows that the active surveillance KL Distance scores did not have an impact on urologists' choice of active surveillance after urologists moved practice, but IMRT KL Distance scores of co-workers after moving had a significant impact on choice of IMRT after a urologist moved to a new practice. These results implied that coworkers' patients selection criteria for active surveillance may not influence treatment choice after moving to a new practice. However, if coworkers' patients selection criteria for active treatment were different from the market average, the physicians would use more of the active treatment.

3.5.3 Targeted location to move

Figure 6 shows that for percentage of treatments, in the period before moving the coworkers after move did not have an impact for any of the treatments. Figure 7 shows that for KL Distance, coworkers after move had a moderate impact on urologists' usage of prostatectomy. This may be measurement errors or this may suggested that urologists moved to the new practices because he/she shared the same patients' selection criteria for prostatectomy. The later hypothesis was consistent with Pollack's findings (Pollack et al. 2012). Pollack et al reported that urologists who preferred prostatectomy treatment were more likely to be in the same network subgroup. My results showed that urologists chose to move to new practices that shared similar prostatectomy usage and patients' selection criteria. It may be possible that my result was the cause for Pollack's findings. For example, because urologists shared the same practice style of prostatectomy moved to practice together, therefore they were in the same network subgroup.

3.5.4 Patients Selection

Urologists may intentionally select patients in order to practice specific skills. For example, young urologists may want to practice surgical skills by admitting more patients who were eligible for prostatectomy. I used Ttest to compare the average probabilities of each treatment and average patients' entropy scores between the urologists who moved and their coworkers in the same period. Average patients' probabilities of active surveillance were lower for urologists who moved compared to his/her coworkers for the period before moving (p=0.03). It may because urologists who moved practice were normally younger and were willing to take more patients suitable for active treatments. However, there were no differences for the average probabilities of active treatments and average entropy scores between urologists who moved and their coworkers in the same periods. Therefore, it seems unlikely that the peer influence after moving to a new practice we had detected was biased by patients' selection by urologist.

3.6 Summary

In this work, I used two types of practice styles to measure peer influence. I showed that peers' impacts of two types of practice styles were different for active treatment, e.g., IMRT. Specifically, for active treatments, coworkers' impact of percentage usage was larger than coworkers' impact of patients' selection criteria.

After a urologist moved to a new practice, if the new coworkers were more aggressive than the market average for the usage of active treatment, this urologist would use more of the same active treatment. Therefore, in order to reduce potential overuse of active treatment, policy makers also may consider use patients' selection criteria as a peer comparison measure.

In addition, I also showed that urologists may select practice location because of specific treatment styles, e.g., prostatectomy. This result may help to explain why urologists who shared the same network had similar usage of usage of prostatectomy for localized prostate cancer patients. Therefore, practice location selection may be a potential bias factor when evaluating peer impacts.

4 Patients' Volume and Financial Impact on Physicians' Active Surveillance Usage Choice

4.1 Introduction

Physicians' treatment choices are related to the reimbursement level (Shahinian, Kuo, and Gilbert 2010a, Clemens and Gottlieb 2014, Danzon, Manning, and Marquis 1984, Jacobson et al. 2010, Lee and Mitchell 1994a, Howard, Hockenberry, and David 2017, Gruber, Kim, and Mayzlin 1999, Nguyen 1996, Gabel and Rice 1985). Most of current research studies were investigating the impact of reimbursement changes on active treatments. It may not be easy to measure the impact of reimbursement changes on the adoption of conservative treatment directly. There are several reasons. First, the reimbursement changes for conservative treatments were not as obvious as the reimbursement changes of active treatments. Second, the reimbursement changes for active treatments may increase, decrease, or do not impact on the usage of conservative treatments. For example, after the reimbursement of high cost procedures decreased, physicians may continue increasing the use of this procedure in order to make up the potential revenue loss, therefore reducing the adoption of conservative treatment. Physician may reduce the usage of the high cost procedure after reimbursement decrease, therefore increasing the adoption of conservative treatment. It may be also possible that the reimbursement change for high cost procedure will not change the usage of conservative treatment because physicians switch to other alternative high cost procedures. Third, each physician has his/her own preference of different treatment methods, and may have a preferred treatment distribution, e.g., the percentage of patients that shall receive specific kinds of treatment. This preference and treatment distribution decided physicians' average treatment reimbursement per patient. The average treatment reimbursement, rather than reimbursement of a particular treatment, decided physicians' net potential revenue gain or loss for adoption of conservative treatment.

Patient volume change may also influence physicians' selection of treatment methods (Gruber and Owings 1996). If patients' volume decrease, physicians may increase the use of expensive procedures to maintain their revenue, therefore reducing the use of conservative treatment. Therefore, patients' volume change may also influence the adoption of conservative treatment.

Active surveillance is an increasingly popular conservative treatment for localized prostate cancer (Liu et al. 2020). Both reimbursements change of high cost procedures and patients' volume change may impact on the adoption of active surveillance. For example, the usage of IMRT for localized prostate cancer had increased because of high reimbursement rate and financial incentives (Jacobs et al. 2012). As a response to the increasing usage, The Centers for Medicare and Medicaid Service had reduced the reimbursement rate for IMRT in 2012 by 15% (CMS 2012). At the same time, because of the prostate cancer screening guideline changes in 2008 and 2012, the number of patients with early stage localized prostate cancer had decreased (Howard 2012, Houston et al. 2018). In this work, I investigated whether physicians' average reimbursement changes of active treatment per patient and the patients' volume changes had an impact the adoption of active surveillance. In subgroup analyses, I estimated whether the reimbursement changes and volume changes had different impact on urologists who had different treatment preferences.

4.2 Treatment Costs and Patients' Volume

4.2.1 Average Cost for Different Treatments

In order to measure the impact of average reimbursement change per patient for each urologist, I need to know the average treatment cost for different treatment methods. I used the Medicare reimbursement of each localized prostate cancer patient to evaluate the treatment costs of different treatments methods. By patients' restriction convention, I used patients with fee for service Medicare at least 12 months before and 12 months after diagnosis date. I summarized patients' medical cost one year before the diagnosis date, and one year after diagnosis date. I then used the cost differences between the year before and the year after as the estimate of the treatment cost for early stage prostate cancer. I excluded the patients with treatment costs outside 5 percentile and 95 percentile for each treatment of the diagnosis year. I inflated the inpatient and outpatient costs to 2016's value by Inpatient Hospital Market Basket Input Price Index of the year (cms.gov 2017, 2020), and I inflated physicians' services costs to 2016's value by Medicare Economic Index (cms.gov 2017, Berndt 2012). Table 1 summarized the annual increase rates of both indexes. I also inflated the healthcare cost by using the "level of the indexes", and results were similar. Specific variables that I included for the calculation of treatment costs for different treatments were in Supplementary File 4.1. Average cost and standard deviation for each treatment method by year of diagnosis was summarized in Table 2.

4.2.2 Patients' Volume

I summarized the localized prostate cancer patients' volume each year by for each urologist. I also restricted patients who had fee for service Medicare 12 months before and 12 months after diagnosis. In the analysis sample, I kept the urologists with equal or more than 10 patients for the year. Urologists may intentionally reduce their patients' volume because of personal reasons, e.g., planning to retire. As a result, I estimated a patients' volume for a urologist using an ordinary least square regression model (Formula 1). The independent variables in the regression model included urologist's patient's volume in the previous year, the patients' volumes of the Health Service Area this urologist practiced at in the current year and in the previous year. The Health Service Area the urologist practiced at each year was identified by the plurality of claims she/he filed for the year. I used this estimated patients' volume as an instrument for the actual patients' volume of the year, and calculated the volume difference between this estimated patients' volume and his patients' volume in the previous year. The results of the volume difference are in Table 3.

$$\text{Formula 1: } Vol_{p,y} = Vol_{p,\,y-1} + Vol_{H,\,y-1} + Vol_{H,\,y} + \varepsilon$$

Vol is patients' volume, p is urologist, H is the Health Service Area, and y is year

4.2.3 Treatment Distribution and Expected Reimbursement Difference

I used the patients' sample between 2005 and 2015 to identify each urologist's distribution of treatment options. The treatment options include: prostatectomy, robotic prostatectomy, IMRT, 3D Conformal radiation therapy, brachytherapy, proton therapy, stereotactic radiation therapy, ADT, Cryotherapy, and active surveillance. The patient sample followed the same patients' restriction criteria as above. I used each urologist's patients' treatment distribution of the previous year and the average treatment costs of the year from Table 2 to evaluate each urologists' expected reimbursement per patient if this urologist followed his previous years' treatment distribution. I calculated the average reimbursement difference between this expected average treatment cost and the actual average treatment cost of this urologist for the year. The results are in Table 3. This cost difference represented that if this urologist used the same treatment distribution as the previous year, the expected average gain or loss per patient this urologist would encounter in the current year. This expected gain or loss was our main interests. I included urologists' previous years' treatment distribution as a factor to calculate the expected reimbursement per patient for each urologist because urologists who had different treatment combination would experience very different expected reimbursement change. For example, a urologist who used IMRT as his/her main treatment method would experience larger average reimbursement reduction per patient compared to a urologist who did not use IMRT as his/her main treatment method between 2012 and 2013, when the reimbursement of IMRT dropped 30%.

4.2.4 Control Variables

I included whether urologist is affiliated with a teaching facility, whether urologist practiced at IMRT self-referral facility, year of diagnosis, patients' probability of undertaking active surveillance, patients' entropy score of different treatment probabilities, and urologists' fixed effect in the model.

I estimated patients' probability of undertaking active treatments and active surveillance by multinomial logistic regression models (Formula 2). The models included patients' age, race/ethnicity, PSA value, Gleason Score, cancer stage, cancer extension, region, Medicaid eligibility status, socioeconomical status, comorbidities, and year of diagnosis. The entropy score of different treatment probabilities were calculated by Formula 3, representing how likely this patient would undertake diversified treatment options. Different treatments for localized prostate cancer may have different clinical outcomes (Hamdy et al. 2016) and side effects (Hoffman et al. 2020), therefore urologist's and patient's preference may influence the final choice of treatment. The entropy score showed how much the treatment choice was influenced by urologist's and patient's personal choice rather than a clear clinical consideration. The larger the entropy score the more likely that this patient may receive different treatments with equal probabilities. Therefore personal preference had a larger impact for patients with higher entropy scores compared to patients with lower entropy scores.

Formula 2:

For patients i treated by urologist j in period t, denote the treatment procedure by Y_{ijt}.

$$Y_{ijt} = \begin{cases} 1, & \text{if patient received surgery;} \\ 2, & \text{IMRT;} \\ 3, & \text{Other;} \\ 4, & \text{AS and None Treatments.} \end{cases}$$

$$ln \frac{Pr(Y_{ijt} = k)}{Pr(Y_{ijt} = 3)} = \beta_0 + \beta_2 \boldsymbol{X_i} + \beta_5 T_i + \epsilon_{ijt}$$

where $k = 1, 2, 4$.

Where X i is the patients' demographic and clinical characteristics, and T is the year fixed effects.

Formula 3: $\text{Entropy}_{i} = -\sum \text{Probility(t)} * \log(\text{Probability (t)})$

Where Probability (t) is the probability of undertaking each of the four treatments for patient i: prostatectomy, IMRT, others, and AS and None Treatment.

4.2.5 Type of Urologists for Subgroup Analysis

For subgroup analyses, I divided urologists by two approaches. The first one was by the most popular treatment the urologist used during the year. For example, if a urologist used prostatectomy more than other kinds of treatment, this urologist was categorized as surgery urologist. I categorized urologists into three groups: surgery urologists, IMRT urologists, and others.

The second subgroup analysis was based on the how much that urologists used a specific treatment approach different from the market average. I used average KL Distance of each urologist for each treatment to measure the scale of the differences. The KL Distance were calculated by Formula 4, and represented that if a urologist chose a specific treatment for his/her patients, how much difference between his/her choice and the treatment probabilities measured by the market average. I was specifically interested in two kinds of urologists: urologists who used prostatectomy more aggressive than others, and urologists who used IMRT more aggressive than others. I categorized urologists by their treatment KL Distance into high, medium, and low groups. For example, the IMRT KL Distance high group used the IMRT more different than the market average than the IMRT KL Distance low group.

$$\text{Formula 4: } KL_T = \sum \text{Probability}_T * \log(\text{Probability}_T / \text{Probability}_{T,i})$$

Where T is the treatment options, including Surgery, IMRT, Others and Active Surveillance and None Treatment. $\text{Probability}_{T,i}$ is the probability of each treatment for patient i calculated by the multinomial logistic regression models described in the "Control Variables" Section. Probability_T is the default probability of the treatment the urologist believed that the patient should undertake if this treatment was selected as the final treatment. I set $\text{Probability}_T = 0.9$ if treatment T is the final selection. $\text{Probability}_{\neq T} = 0.03$ for other three alternatives. The value of "0.9" and "0.03" are my arbitrary choice and may be adjusted for sensitivity checks. By Formula 4, I calculated the KL Distance for the 4 treatment categories separately, e.g., KL Distance of Surgery, KL Distance of IMRT, KL Distance of Others, and KL Distance of Active Surveillance.

4.2.6 Econometrics model

The main purpose of this study was to evaluate the impact of reimbursement and patients' volume changes on urologists' adoption of active surveillance. I adopted an ordinary least square regression model (Formula 5) to estimate patient i's probability of undergoing active surveillance treated by urologist j in period t.

$$\text{Formula 5: } Y_{i,j} = \alpha + X_i + U + \beta1 * \text{Reimdiff}_{j,t} + \beta2 * \text{Voldiff}_{j,t} + \text{Year}_i + \text{error}$$

Y = 1 when patients undertook active surveillance and Y = 0 when patients undertook other treatments. X_i was the patients' characteristics, including the probability of undertaking active surveillance and patient's entropy score. U is urologist's characteristics including teaching affiliation, IMRT self-referral capacities, and urologists' fixed effects. Reimdiff is the difference between the expected reimbursement if urologists followed his/her previous years' treatment distribution and his/her actual average reimbursement for year t. Voldiff is the difference between the expected patients' volume calculated from Formula 1 and his/her actual volume of the previous year.

For my first subgroup analysis, I evaluated whether the impacts of average reimbursement changes and patients' volume changes were the same for different types of urologists. For example, whether urologists used surgery as their major treatment approach or urologists used IMRT as their major treatment approach were influenced by reimbursement and volume changes similarly. I added an interaction term between urologists' type and estimated average reimbursement change, and an interaction term between urologists' type and estimated average volume change in the model (Formula 6). Urologist Type is a categorical variable, with 1 as urologists who used surgery as the major treatment, 2 as urologist who used IMRT as the major treatment, and 3 as urologists used other methods as the major treatment.

$$\text{Formula 6: } Y_{i,,j} = \alpha + X_i + U + \beta1 * \text{Reimdiff}_{j,t} + \beta2 * \text{Voldiff}_{j,t}$$
$$+ \beta3 * \text{Reimdiff}_{j,t}\#\#\text{Urologist Type} + \beta4 * \text{Voldiff}_{j,t}\#\#\text{Urologist Type} + \text{Year}_i + \text{error}$$

In the second subgroup analysis, I evaluated whether the impacts of average reimbursement change were the same for urologists who used IMRT more different from the market average than others, and whether the impacts of average reimbursement change were the same for urologists who used prostatectomy more different from the market average than others (Formula 7). Both "Urologist IMRT KL Distance Group" and "Urologist Prostatectomy KL Distance Group" are categorical variable, dividing the urologists into three groups by tertile. For example, The “Prostatectomy KL Distance Group” high represented the urologists who used prostatectomy the most different from the market average.

$$\text{Formula 7: } Y_{i,,j} = \alpha + X_{i,,t} + U + \beta 1 * \text{Reimdiff}_{j,\,t} + \beta 2 * \text{Voldiff}_{j,\,t} + \beta 3 * \text{Reimdiff}_{j,\,t}\text{##Urologist IMRT KL Distance Group} + \beta 4 * \text{Reimdiff}_{j,\,t}\text{##Urologist Prostatectomy KL Distance Group} + \text{Year}_{i} + \text{error}$$

4.3 Preliminary Results

4.3.1 Treatment Costs

Table 2 summarized the average costs and the standard deviation of different treatments by the diagnosis year. The average treatment costs for prostatectomy were stable between 2004 and 2015. As we expected, the average treatment costs for IMRT experienced the largest decrease between 2011 and 2013. The average treatment cost of prostatectomy, IMRT, 3D Conformal Radiation, and brachytherapy were consistent with the mean cost summarized by Mitchell 2013 (Mitchell 2013). The average treatment cost of ADT was much higher than the mean treatment cost estimated by Shahinian et al. 2010 (Shahinian, Kuo, and Gilbert 2010b). It may be because Shahinian et al., used the actual drug cost per month to estimate treatment cost. I used the difference between the year before and after the diagnosis. My approach may have overestimated the ADT treatment cost because ADT treatment was normally used for palliation treatment or was used to combine with radiation therapies. In this analysis, I used my estimation of the average cost for internal consistency. The standard deviation of treatment AS was large. We already excluded patients without any treatment when evaluating the cost for active surveillance. Therefore, the large standard deviation suggested that the health condition of patients undertaking active surveillance varied. Some patients encountered higher health care cost in the year after diagnosis of prostate cancer.

4.3.2 Changes of Average Reimbursement per Patient and Changes of Patient Volume

Table 3 summarized the average reimbursement changes per patient if the urologists kept the same treatment distribution of the previous year, and the difference between the expected patients’ volume and the year before. The largest decrease for average reimbursement change per patient occurred between 2012 and 2013, which were consistent with the IMRT reimbursement decrease in 2012. The largest decrease in patients’ volume occurred on 2008 (0.9 patient per urologist) and 2012 (1.9 patients per urologist), which were consistent with the localized prostate cancer screening policy changes in these two years.

4.3.3 Impact of Average Patients' Reimbursement and Patients' Volume on Active

My analysis sample included 888 unique urologists and 88,148 patients between 2004 and 2015. Table 4 summarized the number of patients and the percentage of patients undertaking active surveillance by year of diagnosis. In the analysis, I grouped urologists who had less than 61 patients (10% percentile of the all the urologists) into one group as one fixed effect, to increase the power of the model. The results of Formula 5 showed that for every 10,000 USD average reimbursement decrease per patient, the probability of undertaking active surveillance decrease by 1.5 percentage points [95% confidence interval: 0.2%, 2.7%] (Figure 1). The patient volume difference did not have an impact on the adoption of active surveillance. The coefficients, standard errors, and 95% confidence intervals of Formula 5 are in Supplementary Table 2.

4.3.4 Subgroup Analysis

For the first subgroup analysis, I categorized the urologists into three groups based on the most popular treatment methods he/she used for the year. Table 5 summarized the number of urologists and number of patients treated by different types of urologists by year. The number of urologists who used IMRT as his/her major treatment and the number of patients treated by the IMRT urologists had increased by substituting Other Urologists. These trends were consistent with the trend that IMRT were replacing other radiation therapies (Liu et al. 2020). The results of the subgroup analysis (Formula 6) showed that on average patients' probabilities of undertaking active surveillance was 3.21 percentage points [95% confidence interval: 1.49%, 4.91%] less for the urologists using IMRT as their major treatment approach (IMRT urologist), compared to urologists using prostatectomy as their major treatment approach (Prostatectomy urologist). When encountering the same average reimbursement loss per patient, IMRT urologist's probability of using active surveillance was 4.18 percentage points [95% confidence interval: 0.13%, 8.26%] (Figure 1) less than the probability of using active surveillance by Prostatectomy urologist. The coefficients, standard errors, and 95% confidence intervals of Formula 6 are in Supplementary Table 3.

The second subgroup (Formula 7) analyses showed that when encountering the same average reimbursement loss per patient, the probabilities of active surveillance usage for urologists who used IMRT the most different from market average is 3.10 percentage points [95% confidence interval: -0.34%, 6.53%] (p value = 0.075) (Figure 1) less than the urologists who used IMRT the least different from the market average. There were no active surveillance usage differences between urologists who used prostatectomy the most different from the market average compared to urologists who used prostatectomy the least different from the market average when they encountered the same potential loss per patient (Figure 1). The coefficients, standard errors, and 95% confidence intervals of Formula 7 are in Supplementary Table 4.

4.4 Limitations

This work had several limitations. First, Urologists treated other patients in addition to those with localized prostate cancer. Using the differences of the average reimbursement for localized prostate cancer may not be an accurate estimate of urologists' revenue changes between different years. The treatment costs for some methods, e.g., ADT, needs further scrutiny. Second, the patients' volume change between two years were small. Therefore, I may not be able to identify the impact of patients' volume difference on active surveillance adoption. Third, we did not include important urologists' characteristics, e.g., age. Physicians' age was associated with their adoption or de-adoption of specific treatments (Howard and Hockenberry 2019).

4.5 Conclusions and Discussion

Reducing healthcare cost is one of the priorities for health system reform for many of the developed countries (Stabile et al. 2013). In the United States, champions such as Choosing Wisely, are targeting on reducing the overuse of low-value cares, in order to reduce healthcare expenditures. Patients with low-risk cancers may be overtreated (Haymart, Miller, and Hawley 2017). Promoting the appropriate usage of active surveillance treatments for low-risk cancers, such as prostate cancer, breast cancer (Hwang et al. 2019), and thyroid cancer (Brito, Hay, and Morris 2014) may reduce healthcare cost, and may prevent patients from experiencing side effects of unnecessary aggressive treatment. However, conservative treatment for cancer may reduce the revenue for healthcare providers. In this paper, we investigated the impact of urologists' average reimbursement changes on adoption of active surveillance for localized prostate cancer patients. Our results showed that when urologists encountered possible revenue loss because of reimbursement changes over years, they would reduce the adoption of conservative treatment. Based on our results, the Centers for Medicare and Medicaid Services may consider increasing the reimbursement for conservative treatment for specialists in order to promote its usage.

We also found that the impact of potential revenue loss was different among urologists who had different treatment preferences. For example, the urologists who used IMRT as their major treatment method and urologists who used IMRT more aggressively than other urologist were less likely to use active surveillance when encountering the same potential revenue loss. This conclusion was consistent with many of the previous studies that physician-owned ambulatory surgical centers and radiation therapy self-referral facilities were less sensitive to newly updated clinical evidence (Howard, David, and Hockenberry 2017), and were less likely to reduce costly treatment usage after reimbursement decrease (Howard, Hockenberry, and David 2017). Specific financial incentives for these facilities may had influenced the adoption of conservative treatments for low-risk cancers and other diseases.

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List of Figures

Chapter 1

Figure 1.1: Prostate Cancer Screening, Treatment Guidelines, and Clinical Trials

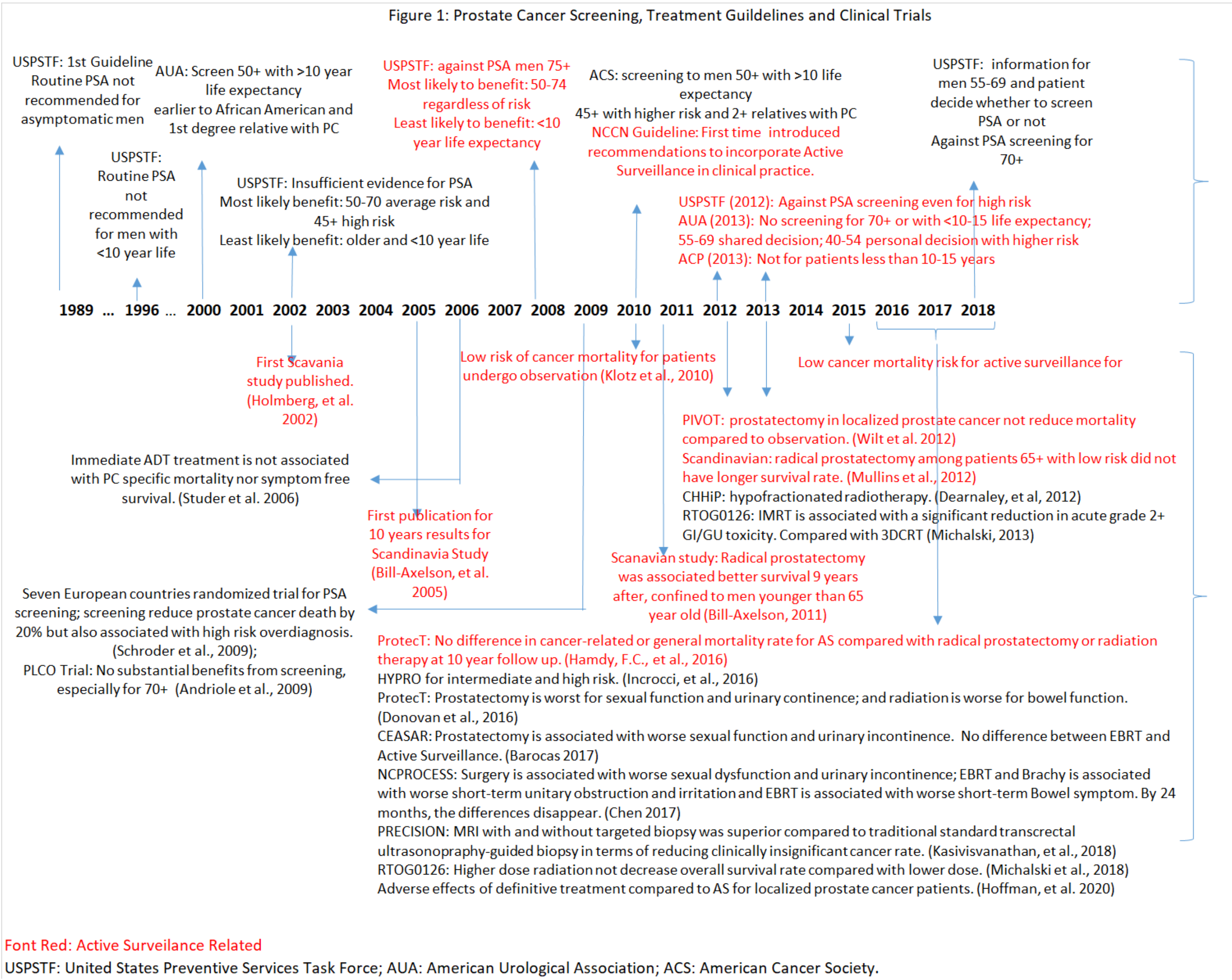
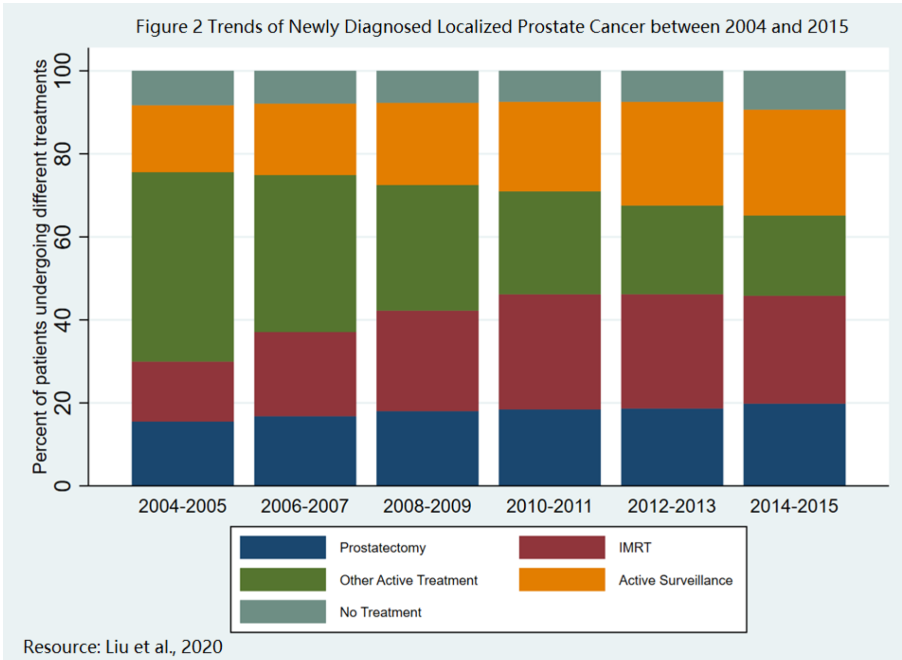


Figure 1.2: Trends of Newly Diagnosed Localized Prostate Cancer Between 2004 and 2015



Chapter 2

Figure 2.1 Patients' Average Entropy Score by Year Diagnosis

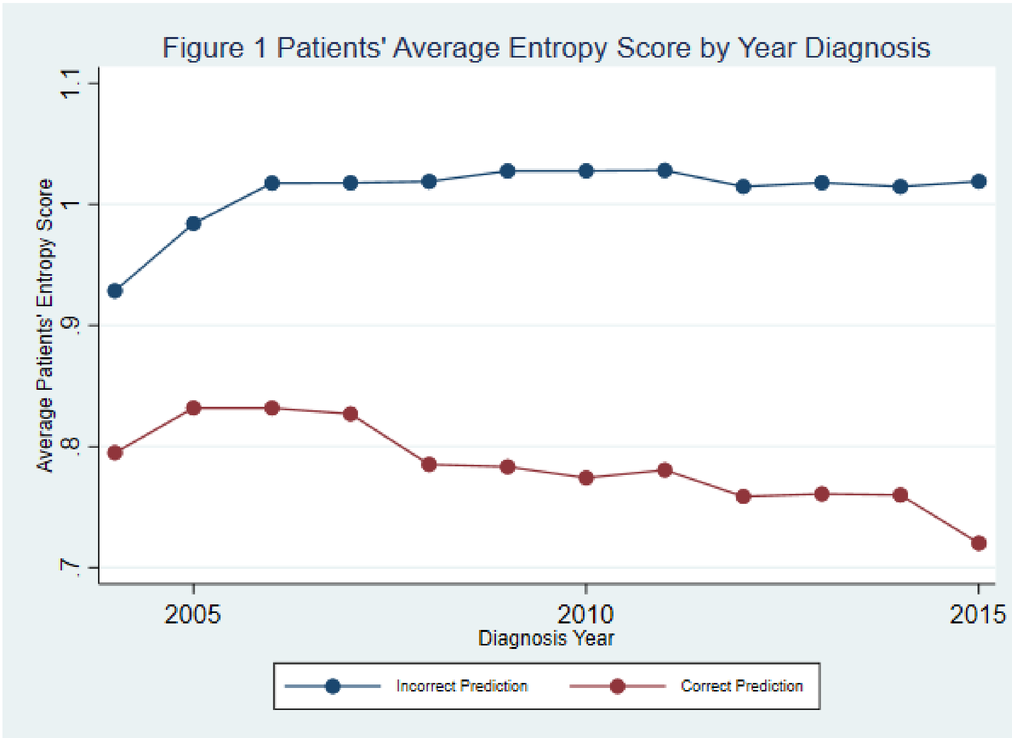


Figure 2.2 Patients' Average Entropy Score by Treatment Option

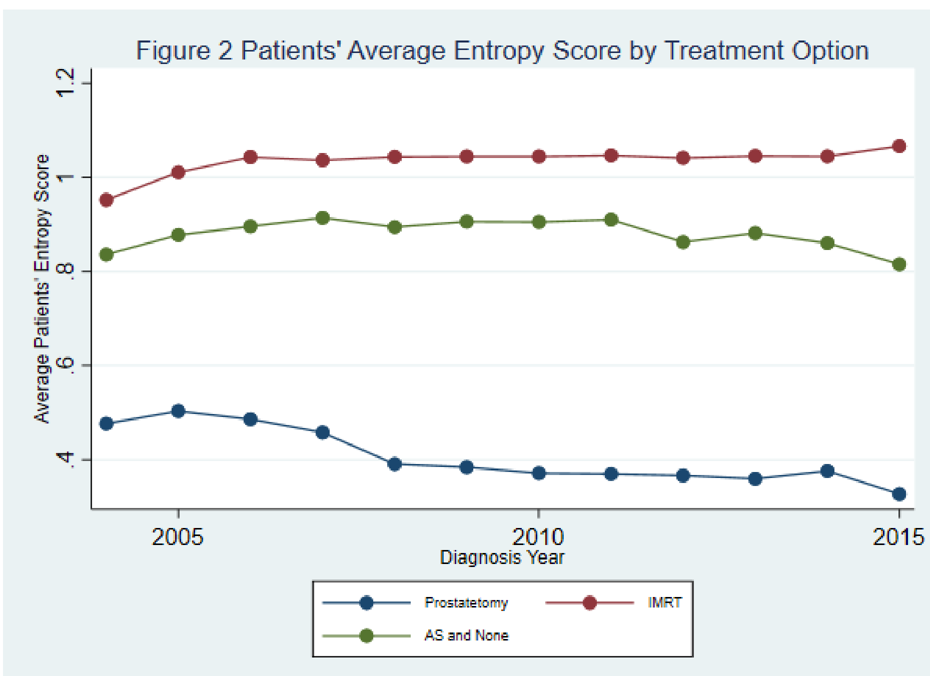


Figure 2.3 Urologists' Average KL Distance Scores by Year Diagnosis

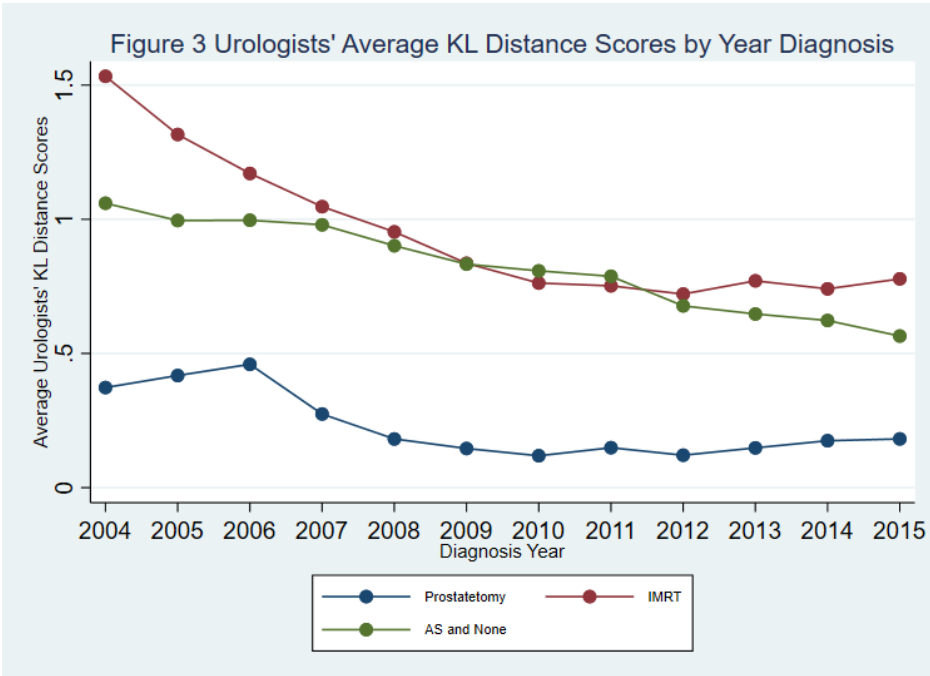


Figure 2.4 Randomly Selected 200 Urologists' Network Graph

Figure 4 Randomly Selected 200 Urologists' Network Graph

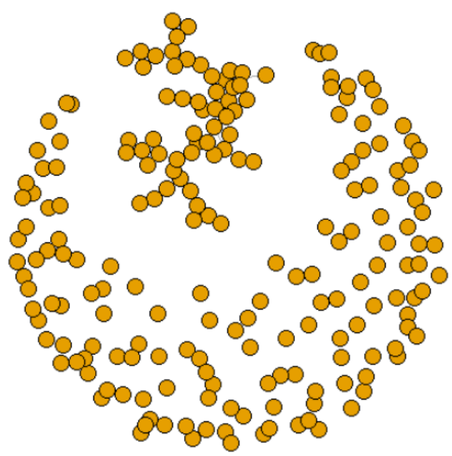


Figure 2.5: Trends of Closeness Centrality Score by Periods

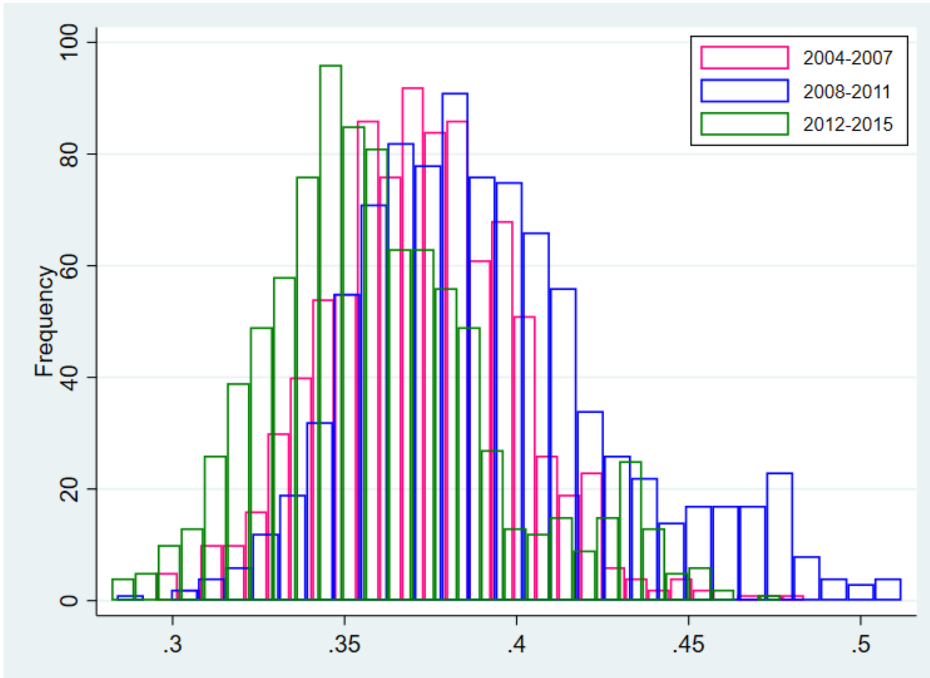


Figure 2.6 Probabilities of Undertaking Prostatectomy, IMRT, Active Surveillance by Network Group

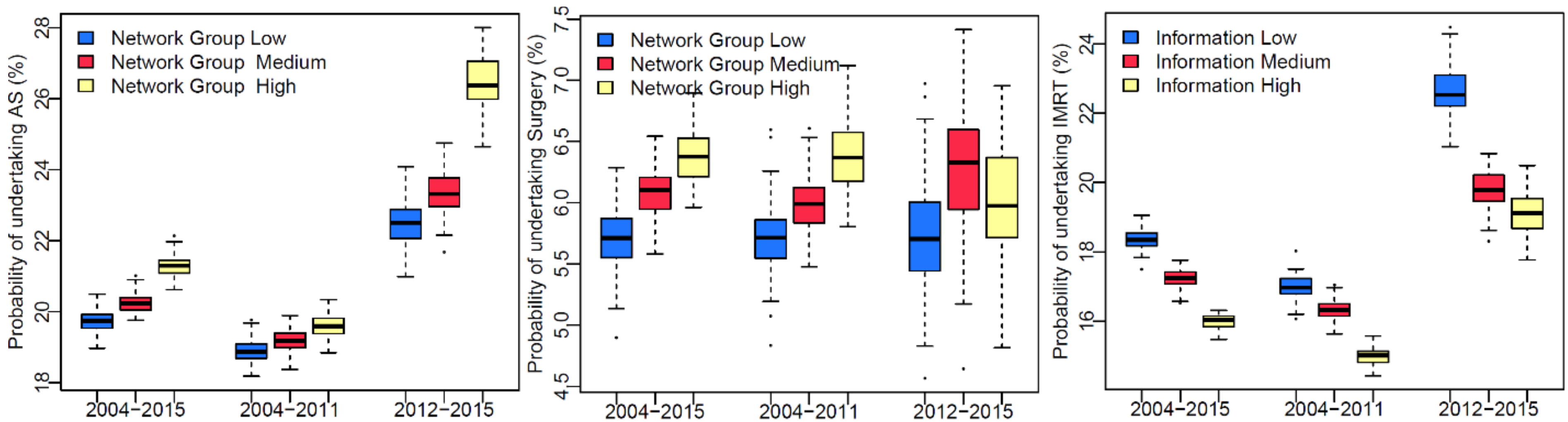


Figure 2.7 Differences of Probabilities of Treatments between Subgroups

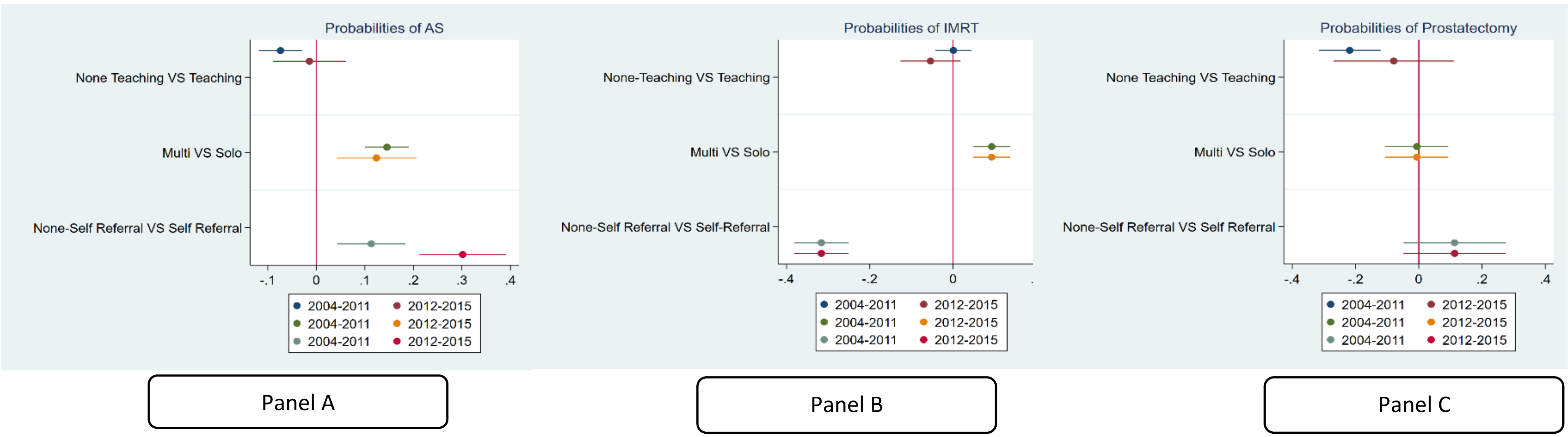
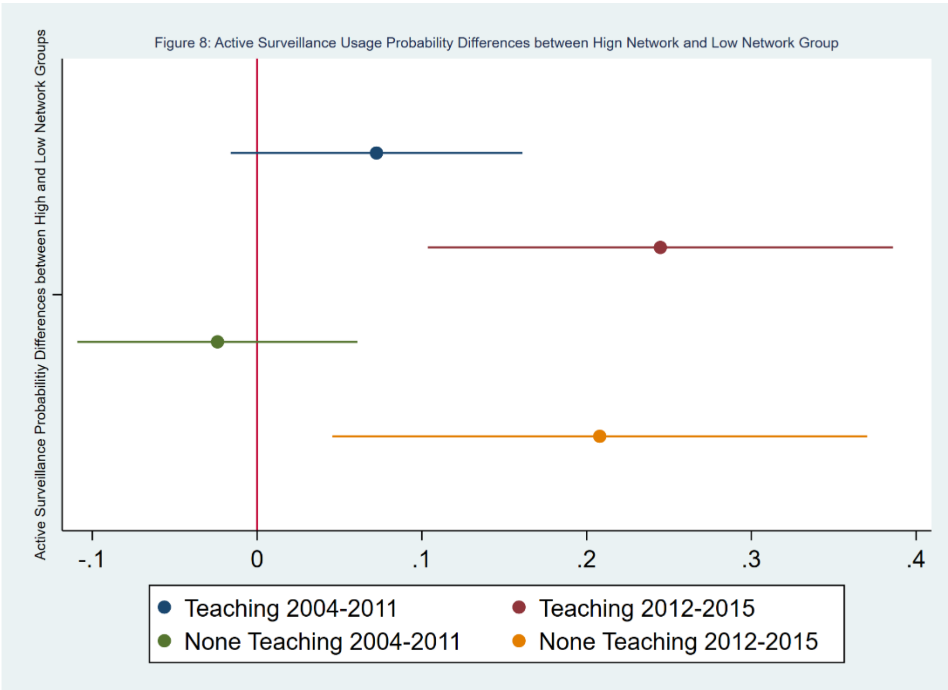

Probabilities of AS
None Teaching VS Teaching
Multi VS Solo
None-Self Referral VS Self Referral
-.1 0 .1 .2 .3 .4
2004-2011 2012-2015
2004-2011 2012-2015
2004-2011 2012-2015
Probabilities of IMRT
None-Teaching VS Teaching
Multi VS Solo
None-Self Referral VS Self-Referral
-.4 -.2 0 .
2004-2011 2012-2015
2004-2011 2012-2015
2004-2011 2012-2015
Probabilities of Prostatectomy
None Teaching VS Teaching
Multi VS Solo
None-Self Referral VS Self Referral
-.4 -.2 0 .2 .4
2004-2011 2012-2015
2004-2011 2012-2015
2004-2011 2012-2015
Panel A
Panel B
Panel C

Figure 2.8 Active Surveillance Usage Probability Differences between High Network and Low Network Group by Teaching Status



Chapter 3

Figure 3.1 Distribution of Year that Urologists Changed Practice

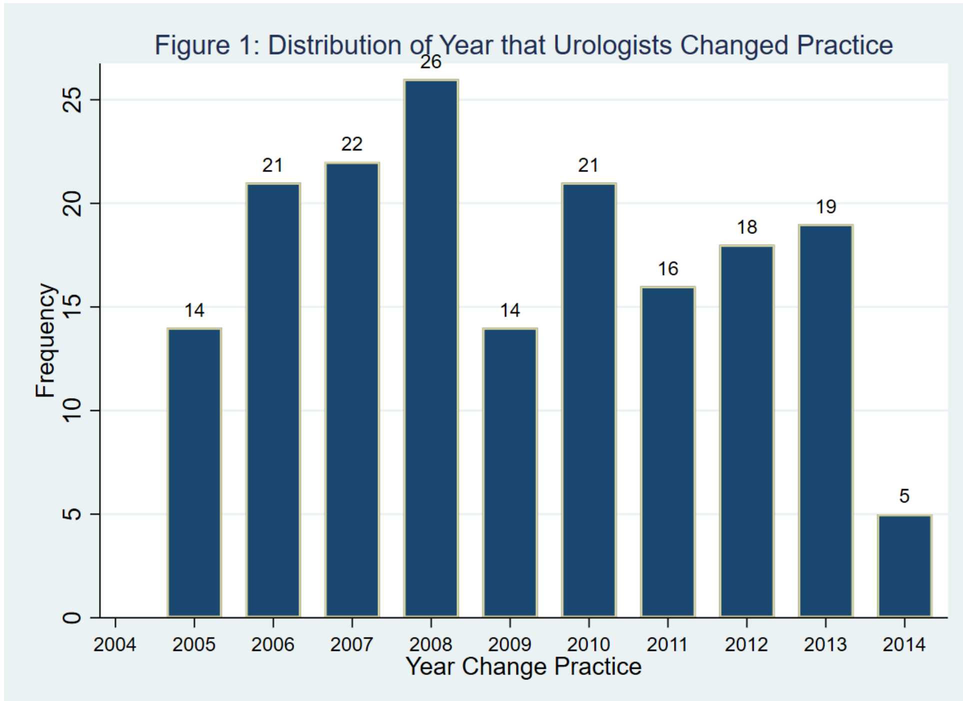


Figure 3.2 Number of Years Practiced Before and After Move

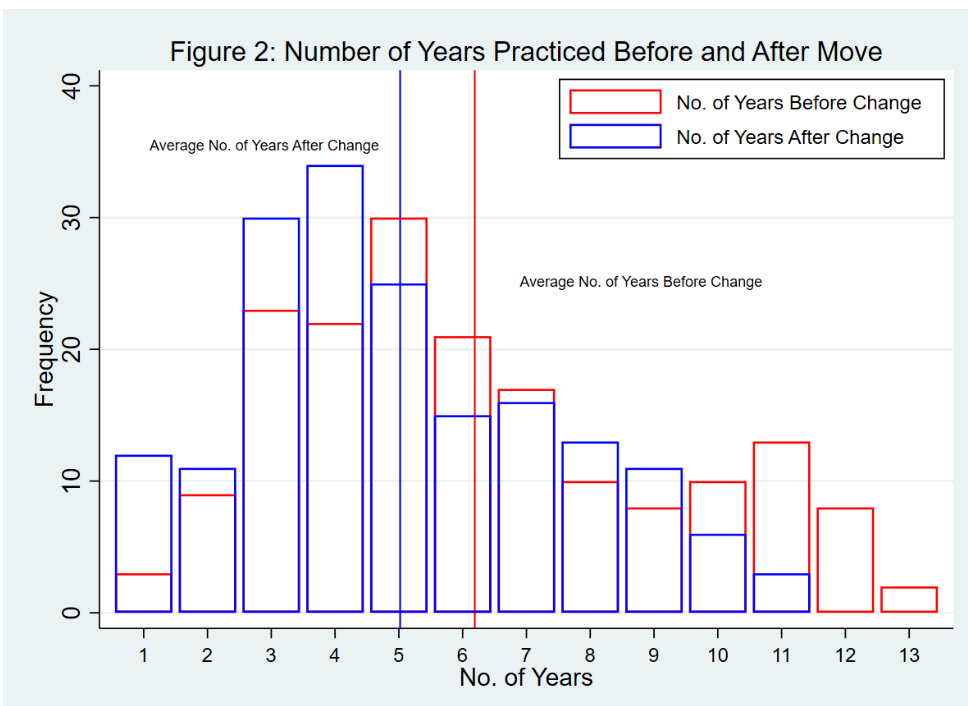


Figure 3.3 Patient Volume by Periods

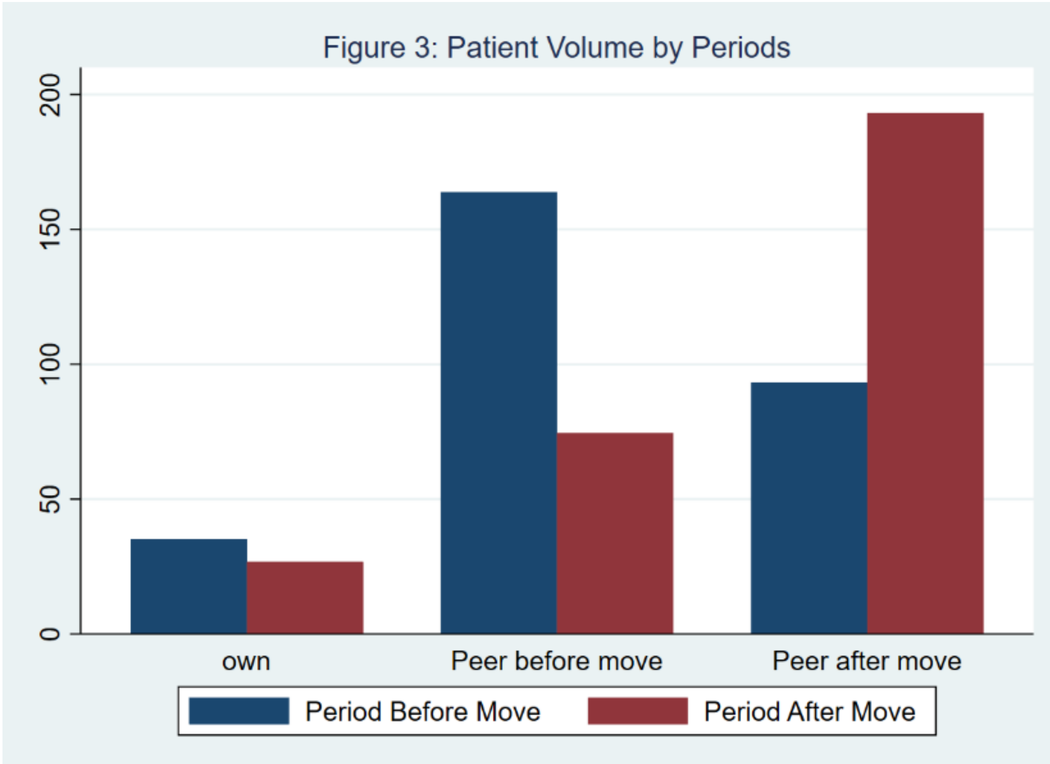


Figure 3.4 Coworkers’ Percentage of Treatment Impact on Treatment Choice

Figure 4: Coworkers' Percentage of Treatment on Treatment Choice

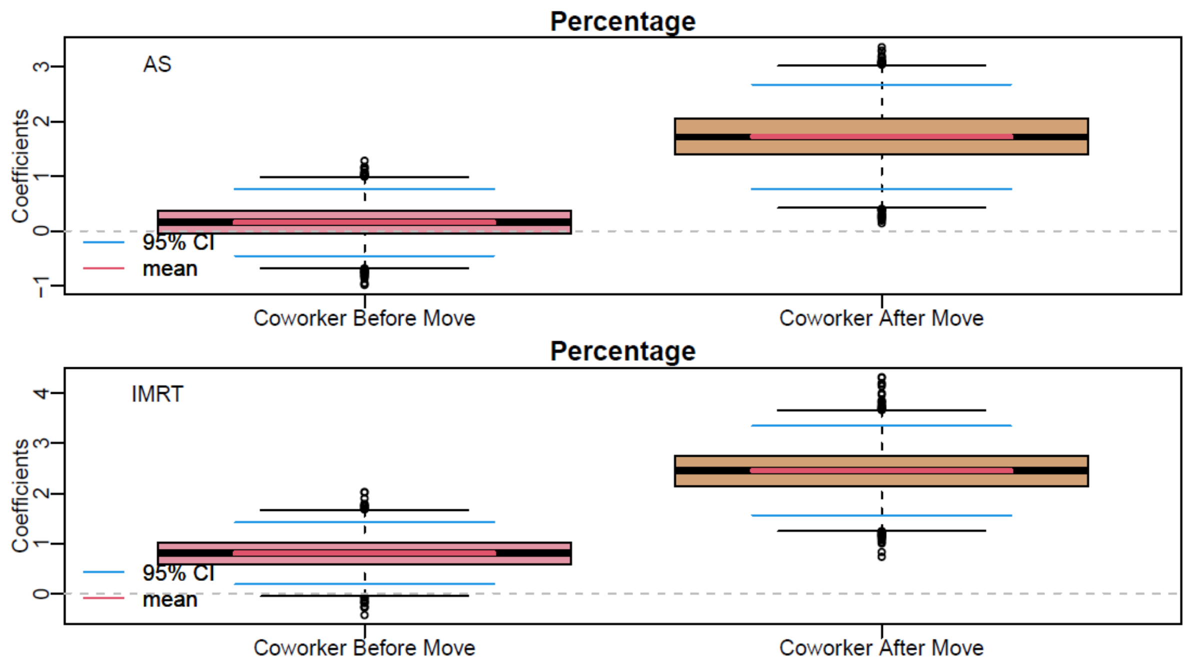


Figure 3.5 Coworkers’ KL Distance Impact on Treatment Choice

Figure 5: Coworkers' KL Distance Impact on Treatment Choice

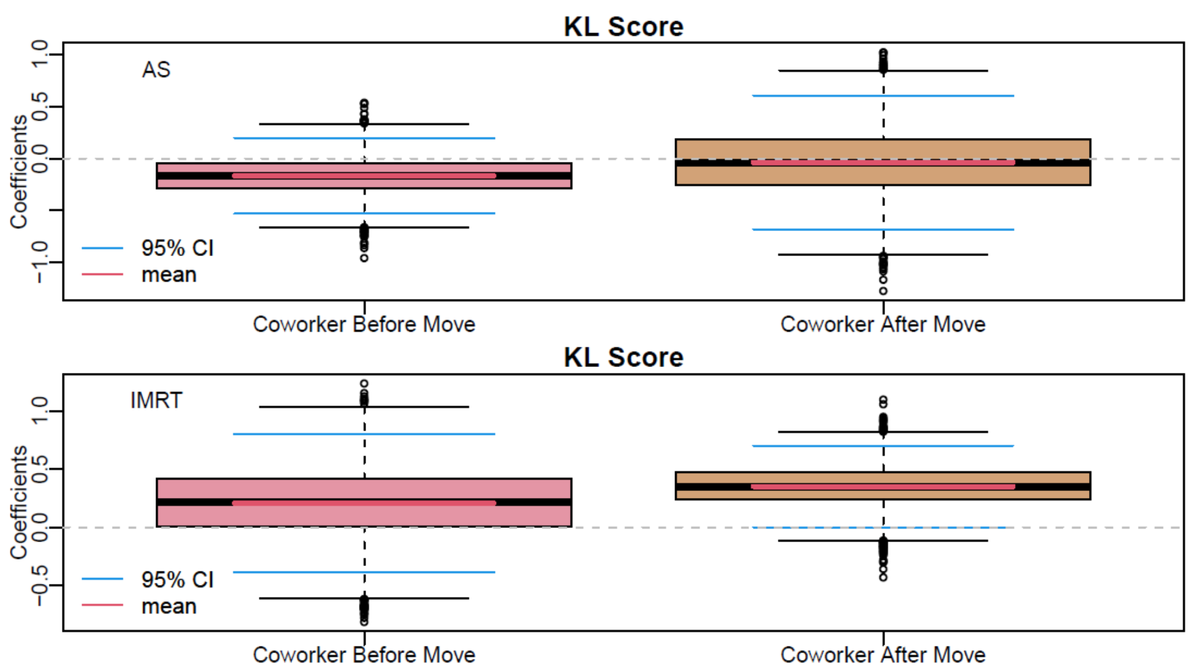


Figure 3.6 Impact of Percentage of Treatment of Coworkers before Move

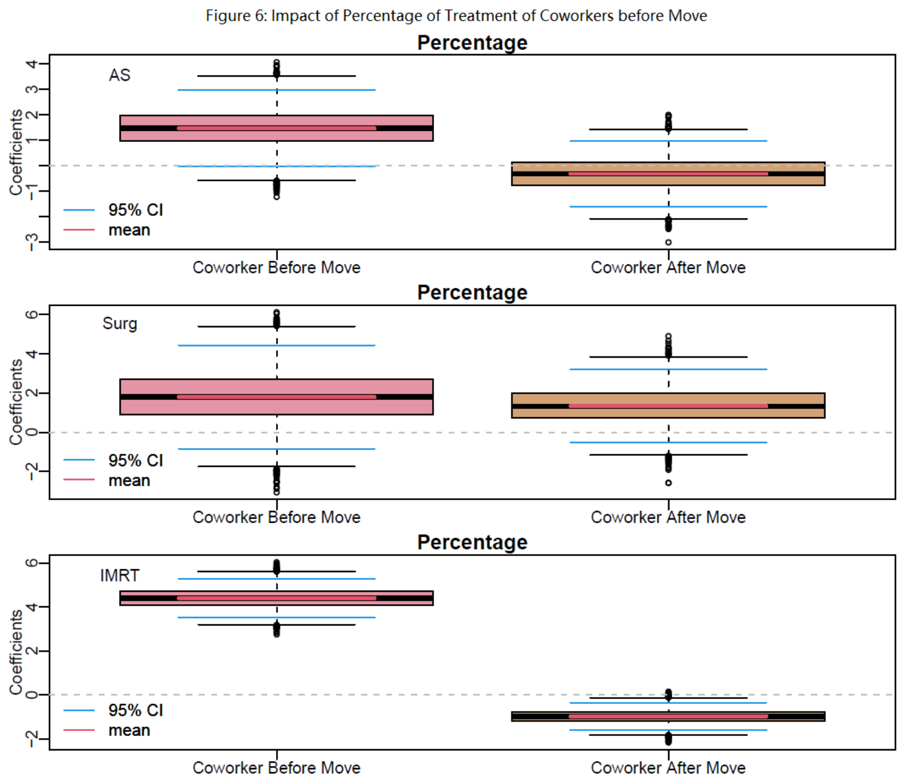
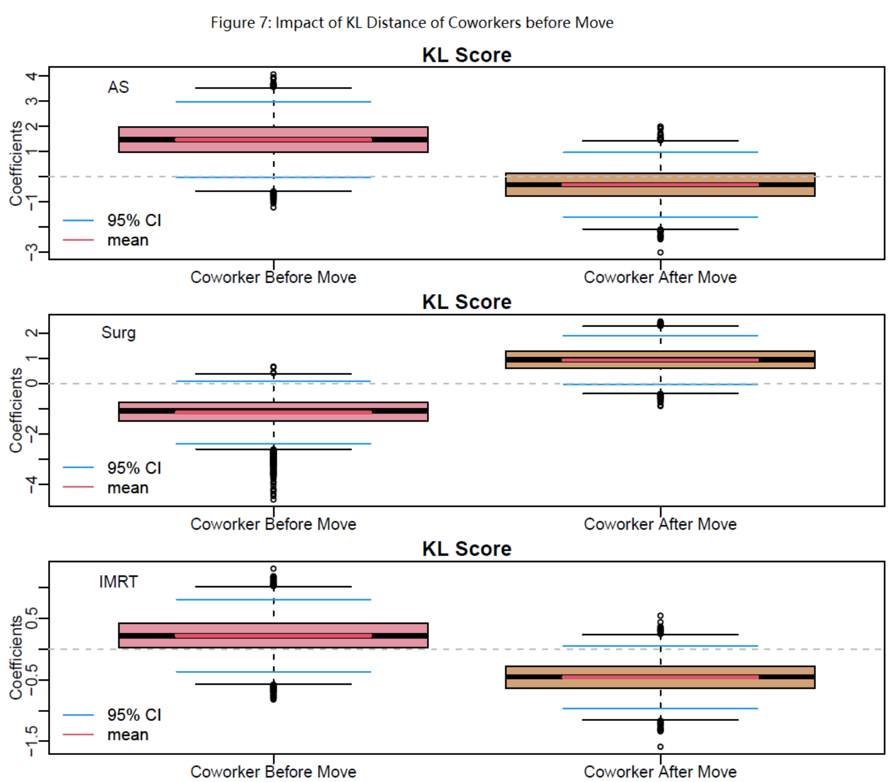
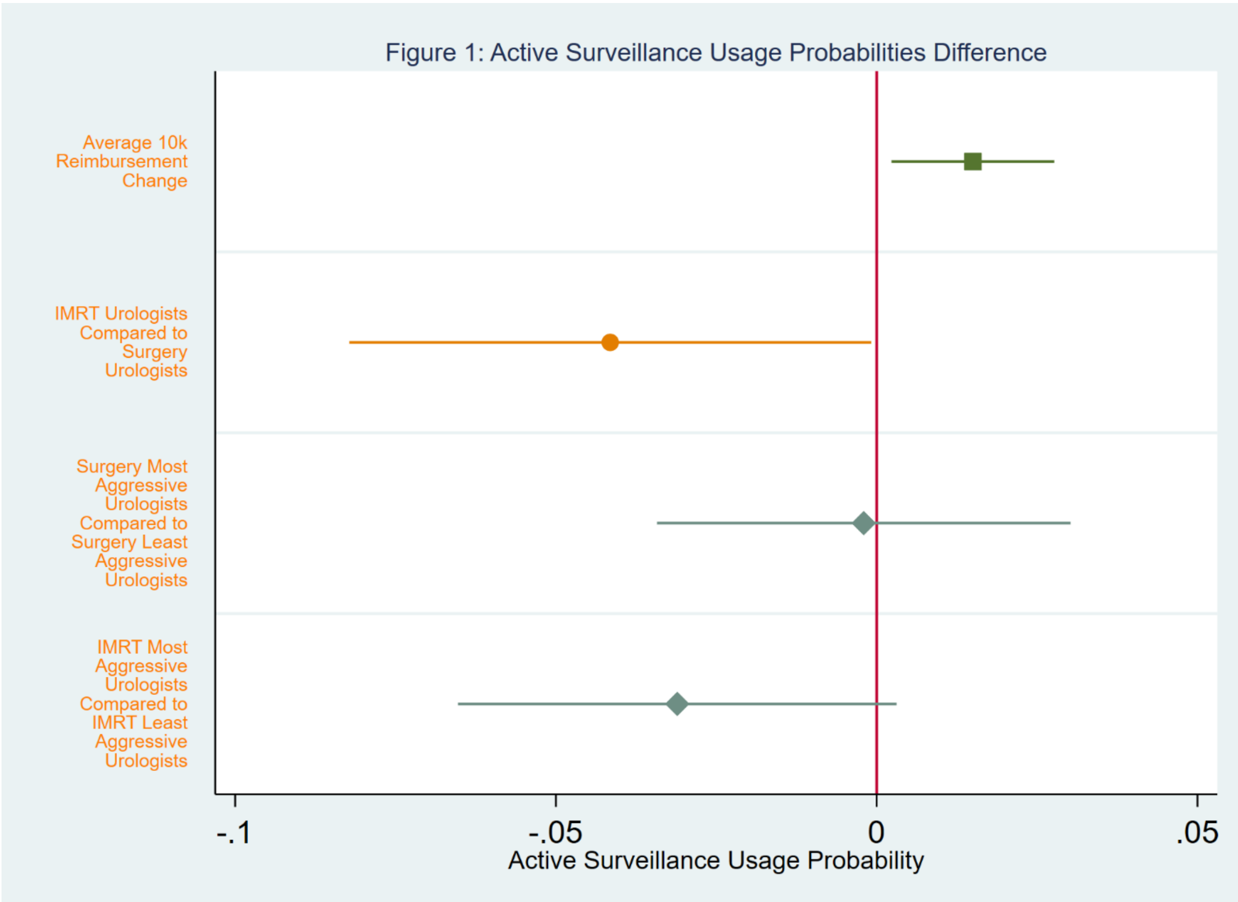


Figure 3.7 Impact of KL Distance of Coworkers before Move



Chapter 4

Figure 4.1 Active Surveillance Usage Probabilities Difference



List of Tables

Chapter 1

Table 1.1: Localized Prostate Cancer Treatment Cost

Table 1: Localized Prostate Cancer Treatment Cost	Average Cost Medicare by (Mitchell, 2013)	Average Cost Commercial (Pan et al., 2017)
Radical prostatectomy	$16,762	
Brachytherapy	$17,076	$29,506
Intensity-modulated radiation therapy (IMRT)	$31,574	$59,012
Androgen deprivation therapy (ADT)	$2,112	
Active Surveillance	$4,228	
Stereotactic (SBS)		$49,504
Three-dimensional conformal radiation therapy	$20,588	
Proton therapy		$115,501

Table 1.2: National Comprehensive Cancer Network (NCCN) 2010 Guidelines Treatment Options for Localized Prostate Cancer

Table 2: National Comprehensive Cancer Network (NCCN) 2010 Guidelines Treatment Options for Localized Prostate Cancer

Rerurrence Risk	Clinical stage	PSA	GS score	GS grade group	Life expectancy	Initial Therapy
Clinically Localized with Very Low Risk	T1a	<10ng/ml	<=6	1	< 20 years	Active Surveillance (AS)
Clinically Localized with Low Risk	T1 to T2a	<10ng/ml	2-6	1	< 10 Years	AS
					> = 10 Years	AS, Radiation Therapy (RT), or Radical Prostatectomy (Surgery)
Clinically Localized with Intermediate Risk	T2b to T2c	10ng - 20ng/ml	3+4 = 7	2	< 10 Years	AS, RT, or Surgery
					> = 10 Years	RT or Surgery
			4+3 = 7	3	< 10 Years	AS, RT, or Surgery
					> = 10 Years	RT or Surgery
Clinically Localized with High Risk	T3a	> 20ng/ml	8-10	4	Any	RT or Surgery
Locally Advanced with Very High Risk	T3b-T4	Any	Any	5 +	Any	RT, Surgery, or Androgen deprivation therapy (ADT)
Locally Advanced with Metastatic	Any	Any	Any	5 +	Any	ADT or RT

PSA: prostate-specific antigen; GS: Gleason score.

Chapter 2

Table 2.1: Summary Statistics of Patients' Characteristics by Treatment Options

	Prostatectomy	IMRT	Other	ASNone	Total
2004	2908	2427	9105	4509	18949
	(15.3)	(12.8)	(48.1)	(23.8)	(100.0)
2005	2733	2891	7572	4533	17729
	(15.4)	(16.3)	(42.7)	(25.6)	(100.0)
2006	3066	3522	7290	4695	18573
	(16.5)	(19.0)	(39.3)	(25.3)	(100.0)
2007	3131	3952	6672	4648	18403
	(17.0)	(21.5)	(36.3)	(25.3)	(100.0)
2008	2959	3749	5254	4457	16419
	(18.0)	(22.8)	(32.0)	(27.1)	(100.0)
2009	2730	3870	4265	4253	15118
	(18.1)	(25.6)	(28.2)	(28.1)	(100.0)
2010	2743	3913	3625	4140	14421
	(19.0)	(27.1)	(25.1)	(28.7)	(100.0)
2011	2756	3970	3479	4345	14550
	(18.9)	(27.3)	(23.9)	(29.9)	(100.0)
2012	2189	3119	2494	3708	11510
	(19.0)	(27.1)	(21.7)	(32.2)	(100.0)
2013	2170	2913	2234	3692	11009
	(19.7)	(26.5)	(20.3)	(33.5)	(100.0)
2014	2063	2786	2164	3596	10609
	(19.4)	(26.3)	(20.4)	(33.9)	(100.0)
2015	2492	2972	2146	4357	11967
	(20.8)	(24.8)	(17.9)	(36.4)	(100.0)
66-74	27856	22146	27431	26934	104367
	(26.7)	(21.2)	(26.3)	(25.8)	(100.0)
75+	4084	17938	28869	23999	74890
	(5.5)	(24.0)	(38.5)	(32.0)	(100.0)
Black	2254	4623	6405	6369	19651
	(11.5)	(23.5)	(32.6)	(32.4)	(100.0)
White	27356	32586	46185	41237	147364
	(18.6)	(22.1)	(31.3)	(28.0)	(100.0)
Other Races	2330	2875	3710	3327	12242
	(19.0)	(23.5)	(30.3)	(27.2)	(100.0)
Klabunde Comorbidity 0	22104	21979	31198	25760	101041
	(21.9)	(21.8)	(30.9)	(25.5)	(100.0)
klabunde Comorbidity 0-3	8197	13985	18573	14474	55229
	(14.8)	(25.3)	(33.6)	(26.2)	(100.0)
klabunde Comorbidity 3+	1150	3761	5924	5183	16018
	(7.2)	(23.5)	(37.0)	(32.4)	(100.0)
klabunde Comorbidity Unknown	489	359	605	5516	6969
	(7.0)	(5.2)	(8.7)	(79.2)	(100.0)
Not Medicaid	30168	36855	51377	46805	165205
	(18.3)	(22.3)	(31.1)	(28.3)	(100.0)

Medicaid	1772 (12.6)	3229 (23.0)	4923 (35.0)	4128 (29.4)	14052 (100.0)
Rural	3125 (16.5)	4102 (21.7)	6707 (35.4)	4993 (26.4)	18927 (100.0)
Urban	28788 (18.0)	35920 (22.4)	49520 (30.9)	45834 (28.6)	160062 (100.0)
Rural/Urban Unknown	27 (10.1)	62 (23.1)	73 (27.2)	106 (39.6)	268 (100.0)
SES Low	8650 (15.2)	12484 (22.0)	19197 (33.8)	16513 (29.0)	56844 (100.0)
SES Medium	10709 (18.1)	12738 (21.5)	19034 (32.1)	16787 (28.3)	59268 (100.0)
SES High	11880 (20.1)	14065 (23.8)	16791 (28.4)	16364 (27.7)	59100 (100.0)
SES Unknown	701 (17.3)	797 (19.7)	1278 (31.6)	1269 (31.4)	4045 (100.0)
GS Unknown	736 (27.1)	257 (9.5)	519 (19.1)	1206 (44.4)	2718 (100.0)
GS<=6	9461 (13.0)	12000 (16.5)	20434 (28.0)	31000 (42.5)	72895 (100.0)
GS>=7	21743 (21.0)	27827 (26.8)	35347 (34.1)	18727 (18.1)	103644 (100.0)
PSA Value < 10ng/ml	22715 (21.3)	25449 (23.8)	30871 (28.9)	27826 (26.0)	106861 (100.0)
PSA Value >= 10ng/ml	5421 (12.6)	11326 (26.2)	16784 (38.9)	9659 (22.4)	43190 (100.0)
PSA Unknown	3804 (13.0)	3309 (11.3)	8645 (29.6)	13448 (46.0)	29206 (100.0)
Extension Clinically Inapparent Tumor	18348 (17.4)	23958 (22.7)	31284 (29.6)	32072 (30.4)	105662 (100.0)
Extension Clinically Apparent Tumor	7568 (23.5)	8176 (25.4)	10167 (31.6)	6305 (19.6)	32216 (100.0)
Extension Unknown Clinically Apparent	5074 (14.1)	6510 (18.0)	12707 (35.2)	11784 (32.7)	36075 (100.0)
Extension Beyond Prostate	934 (17.9)	1432 (27.4)	2106 (40.3)	748 (14.3)	5220 (100.0)
T4 No Information of Extension	3 (11.5)	6 (23.1)	14 (53.8)	3 (11.5)	26 (100.0)
No evidence or Unknown	13 (22.4)	2 (3.4)	22 (37.9)	21 (36.2)	58 (100.0)
Size Does not meet AJCC Staging Criteria	1633 (1.2)	38892 (28.3)	52165 (38.0)	44523 (32.4)	137213 (100.0)
Size Meet AJJC Staging Criteria	28172 (85.6)	147 (0.4)	420 (1.3)	4167 (12.7)	32906 (100.0)

Prostatectomy after Neoadjuvant Therapy or Unknown	2135	1045	3715	2243	9138
	(23.4)	(11.4)	(40.7)	(24.5)	(100.0)
Stage Very Low Risk	1044	23844	30842	29012	84742
	(1.2)	(28.1)	(36.4)	(34.2)	(100.0)
Low Risk	3019	2623	2962	3180	11784
	(25.6)	(22.3)	(25.1)	(27.0)	(100.0)
Intermediate Risk	19411	12157	20273	17184	69025
	(28.1)	(17.6)	(29.4)	(24.9)	(100.0)
High Risk	7815	928	1039	1055	10837
	(72.1)	(8.6)	(9.6)	(9.7)	(100.0)
Unknown Risk	651	532	1184	502	2869
	(22.7)	(18.5)	(41.3)	(17.5)	(100.0)
South	7013	10262	16071	12048	45394
	(15.4)	(22.6)	(35.4)	(26.5)	(100.0)
North Central	3806	4322	7937	5986	22051
	(17.3)	(19.6)	(36.0)	(27.1)	(100.0)
Northeast	4527	11923	10100	8830	35380
	(12.8)	(33.7)	(28.5)	(25.0)	(100.0)
Pacific/West	16594	13577	22192	24069	76432
	(21.7)	(17.8)	(29.0)	(31.5)	(100.0)
Total	31940	40084	56300	50933	179257
	(17.8)	(22.4)	(31.4)	(28.4)	(100.0)
N	179257				

Table 2.2 Prediction Accuracy Rate by Treatment and Year Diagnosis

Table 2: Prediction Accuracy Rate by Treatment and Year Diagnosis				
Year Diagnosis	Prostatetomy	IMRT	Other Treatment	AS and None Treatment
2004	86%	0%	95%	30%
2005	86%	1%	91%	34%
2006	84%	10%	85%	39%
2007	91%	21%	77%	43%
2008	93%	26%	64%	53%
2009	95%	44%	45%	59%
2010	95%	61%	26%	63%
2011	95%	64%	22%	66%
2012	95%	68%	15%	70%
2013	94%	68%	12%	71%
2014	94%	68%	14%	72%
2015	90%	70%	12%	76%

Table 2.3 Analysis Sample Selection Process

Table 3: Analysis Sample Selection Process		
Prostate cancer diagnosed between January 1st 2001 and December 31st 2015		704,751
	Diagnosis reporting source was hospice/nursing home, autopsy report, or death certificate, as well as patients whose diagnosis date was after the date of death	6,665
	Older than 66 when diagnosed	243,222
	Not met Medicare enrollment criteria	178,262
	Not localized/regional	31,986
	Grade other than level I, II or III	8,083
Total patients diagnosed between 2001 and 2015 met selection criteria		236,533
	Diagnosis between 2001 and 2003	57,276
Total patients diagnosed between 2004 and 2015 met selection criteria		179,257
	Urologists' NPI or UPIN was missing	21,635
	Urologists had less than 10 patients any of the three periods	61,562
	Urologists' teaching affiliation unknown	5,550
	Urologists' other missing variables	2,702
Total Analysis Sample		87,808

Table 2.4 Correlations between KL Distance and Treatment Usage Percentage, Aggregated Patients' Entropy Score, and Patients' Volume

Table 4: Correlations between KL Distance and Treatment Usage Percentage, Aggregated Patients' Entropy Score, and Patients' Volume

	Prostatetomy Usage Percentage			Aggregated Patients' Entropy			Patients' Volume		
	2004-2007	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**
Prostatetomy KL Scores	-0.0284	-0.0527	-0.0527	0.3025	0.1979	0.2335	0.0215	0.0392	0.0418

	IMRT Usage Percentage			Aggregated Patients' Entropy			Patients' Volume		
	2004-2007	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**
IMRT KL Scores	-0.1221	-0.1169	-0.0517	-0.1651	-0.0686	-0.0964	0.0679	0.0967	0.0532

	AS None Percentage			Aggregated Patients' Entropy			Patients' Volume		
	2004-2007	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**	**2004-2007**	**2008-2011**	**2012-2015**
AS None Scores	-0.0039	-0.0289	-0.0344	0.0087	0.0623	0.1626	-0.0356	-0.0172	-0.0129

Table 2.5 Correlations between Different KL Distance Scores

Table 5: Correlations between Different KL Distance Scores

	Prostatetomy			IMRT		
	2004-2007	2008-2011	2012-2015	2004-2007	2008-2011	2012-2015
Prostatectomy	1	1	1			
IMRT	0.0153	0.0067	-0.0299	1	1	1
AS None	-0.0199	-0.0288	-0.0108	-0.0378	-0.1057	-0.1029

Table 2.6 Correlations between Different Usage Percentages

Table 6: Correlations between Different Usage Percentages

	Prostatetomy			IMRT		
	2004-2007	2008-2011	2012-2015	2004-2007	2008-2011	2012-2015
Prostatectomy	1	1	1			
IMRT	-0.2131	-0.3398	-0.3654	1	1	1
AS None	-0.1206	-0.2024	-0.2644	-0.1954	-0.3337	-0.3997

Table 2.7: Summary Statistics of Analysis Sample by Network Group

		Network Group			
		Low	Medium	High	Total
Treatment	Prostatectomy Treatment Volume*	4704	5545	5885	16134
		(16)	(19)	(20)	(18)
	IMRT Treatment Volume	7098	6818	7131	21047
		(24)	(23)	(24)	(24)
	Other Treatment Volume	10211	9992	9151	29354
		(35)	(34)	(31)	(33)
	AS and None Treatment Volume	7267	6946	7060	21273
		(25)	(24)	(24)	(24)
Teaching Affiliation	Affiliated with Teaching Institutes	13027	16145	15622	44794
		(45)	(55)	(54)	(51)
	Not Affiliated with Teaching Institutes	16253	13156	13605	43014
		(56)	(45)	(47)	(49)
Practice Type	Solo Practice	11317	8816	10574	30707
		(39)	(30)	(36)	(35)
	Multi-urologists Practice	17963	20485	18653	57101
		(61)	(70)	(64)	(65)
	Not IMRT self-referral facility	25796	26336	22967	75099
		(88)	(90)	(79)	(86)
	IMRT self-referral facility	3484	2965	6260	12709
		(12)	(10)	(21)	(15)
	Age 66-74	17119	16805	16862	50786
		(59)	(57)	(58)	(58)
	Non-Hispanic Black	3648	2970	2758	9376
		(13)	(10)	(9)	(11)
	Non-Hispanic White	23879	24514	24782	73175
		(82)	(84)	(85)	(83)
	GS<=6	11815	11820	11977	35612
		(40)	(40)	(41)	(41)
	GS>=7	17079	17061	16847	50987
		(58)	(58)	(58)	(58)
	Comorbidity 0	16628	17005	17269	50902
		(57)	(58)	(59)	(58)
	Comorbidity 0-3	9534	9390	9244	28168
		(33)	(32)	(32)	(32)
	Comorbidity 3+	2872	2693	2486	8051
		(10)	(9)	(9)	(9)
	SES Low	12663	8320	5863	26846
		(43)	(28)	(20)	(31)
	SES Medium	10314	10436	8188	28938
		(35)	(36)	(28)	(33)
	SES High	5629	9963	14549	30141
		(19)	(34)	(50)	(34)

	Medicaid	2219 (8)	1804 (6)	1785 (6)	5808 (7)
Aggregated patients' probabilities of Treatment	Average Patients' Probability of Prostatectomy	16%	18%	20%	
	Average Patients' Probability of IMRT	23%	22%	24%	
	Average Patients' Probability of AS None	28%	26%	26%	
	Average Patients' Entropy Score	0.90	0.89	0.87	
Average Urologist Level and Market Level Characteristics	Average Patients' volume	40.46	47.04	47.93	
	Average Number of coworkers	4.63	4.88	4.18	
	Average Prostatectomy KL Scores	0.29	0.26	0.22	
	Average IMRT KL Scores	0.98	1.00	0.91	
	Average AS and None Treatment KL Scores	0.80	0.86	0.88	
	Average HHI	0.17	0.10	0.06	
	Total	29280	29301	29227	87808

* Column percentage

Table 2.8 Patients' Probabilities of Undertaking Active Surveillance by Different Network Groups and Periods

Table 8: Patients' Probabilities of Undertaking Active Surveillance by Different Network Groups and periods		
2004-2015		
Network Low	Network Medium	Network High
19.74% (19.15%, 20.33%)	20.24% (19.72%, 20.77%)	21.29% (20.72%, 21.85%)
2004-2011		
Network Low	Network Medium	Network High
18.89% (18.26%, 19.51%)	19.17% (18.56%, 19.78%)	19.61% (18.98%, 20.26%)
2012-2015		
Network Low	Network Medium	Network High
22.53% (21.25%, 23.80%)	23.36% (22.18%, 24.54%)	26.44% (25.07%, 27.81%)
95% Confidence Interval in Bracket		

Table 2.9 T-Test Network Scores for Different Groups of Urologists

Table 9: T-Test Network Scores for Different Groups of Urologists					
Group	Observation	Mean Closeness Score	Std. Dev.	t value	P value
Teaching	1,334	0.3782	0.0355	4.3104	Pr (teaching > None teaching) = 0.0000
None-Teaching	1,177	0.3721	0.0357		
Solo Practice	855	0.3736	0.0383	-1.8153	Pr (multi > solo) = 0.0348
Multi Practice	1,644	0.3764	0.0342		
None IMRT Self referral	2,102	0.3735	0.0344	-5.8457	Pr (Self Referral > None Self Referral) = 0.000
IMRT Self referral	409	0.3847	0.0405		

Chapter 3

Table 3.1: Patients' Characteristics Before and After Urologists' Move

	Before Change*	After Change	Total
GS Unknown	29	27	56
	(1)	(1)	(1)
GS<=6	2500	1824	4324
	(41)	(39)	(40)
GS>=7	3651	2852	6503
	(59)	(61)	(60)
66-74	3563	2888	6451
	(58)	(61)	(59)
75+	2617	1815	4432
	(42)	(39)	(41)
Black	512	377	889
	(8)	(8)	(8)
White	5167	3917	9084
	(84)	(83)	(84)
Other Races	501	409	910
	(8)	(9)	(8)
Comorbidity 0	3788	2724	6512
	(61)	(58)	(60)
Comorbidity 0-3	1883	1542	3425
	(31)	(33)	(32)
Comorbidity 3+	451	393	844
	(7)	(8)	(8)
Comorbidity Unknown	58	44	102
	(2)	(1)	(2)
Rural	599	354	953
	(10)	(8)	(9)
Urban	5575	4344	9919
	(90)	(92)	(91)
Unknown	6	5	11
	(0)	(0)	(0)
Not Medicaid	5825	4394	10219
	(94)	(93)	(94)
Medicaid	355	309	664
	(6)	(7)	(6)
SES Low	1611	1254	2865
	(26)	(27)	(26)
SES Medium	2131	1597	3728
	(35)	(34)	(34)
SES High	2303	1749	4052

	(37)	(37)	(37)
SES Unknown	135	103	238
	(2)	(2)	(2)
N	6180	4703	10883
Average Patients' Probability of Undertaking Prostatectomy	21%	23%	
Average Patients' Probability of Undertaking IMRT	21%	24%	
Average Patients' Probability of Undertaking Active Surveillance and None Treatment	23%	30%	
Average Patients' Entropy Score	0.87	0.85	

* Column Percentage

Table 3.2 Characteristics of Urologists' Own and Coworker Practice Style

Table 2: Characteristics of Urologists' Own and Co-worker Practice Style						
		Before Move			After Move	
	Own	Coworker before move	Coworker after move	Own	Coworker before move	Coworker after move
Percentage of Prostatetomy*	22.18% (14.33%)	20.45% (10.11%)	22.38% (16.84%)	24.49% (18.27%)	23.11% (14.48%)	20.42% (13.94%)
Percentage of IMRT	18.16% (14.77%)	20.54% (12.90%)	21.23% (17.24%)	23.58% (19.08%)	23.50% (13.69%)	24.33% (16.26%)
Percentage of AS and None Treatment	23.58% (12.66%)	24.20% (8.72%)	25.16% (12.36%)	27.98% (15.42%)	29.31% (10.29%)	29.63% (16.35%)
Urologist Level Treatment Entropy Score#	1.14 (0.23)	1.24 (0.17)	1.15 (0.28)	1.12 (0.22)	1.16 (0.25)	1.24 (0.15)
Average Prostatectomy KL Scores	0.36 (0.73)	0.36 (0.37)	0.34 (0.30)	0.32 (0.62)	0.31 (0.24)	0.29 (0.12)
Average IMRT KL Scores	0.86 (0.42)	0.89 (0.25)	0.86(0.27)	0.70 (0.44)	0.71 (0.18)	0.74 (0.28)
Average AS and None Treatment KL Scores	0.87 (0.60)	0.87 (0.22)	0.89 (0.35)	0.61 (0.52)	0.67 (0.28)	0.62 (0.16)

* Standard deviation in bracket

\# Urologist level treatment entropy represents how diversified a urologist used different treatment.

Table 3.3 Odds Ratio of Practice Style Impact by Being Coworker

Table 3: Odds Ratio of Practice Style Impact by Being Coworker				
	AS		IMRT	
	Coworker Before Move	Coworker After Move	Coworker Before Move	Coworker After Move
Percentage	18.36 (1.24, 271.98)*	34.67 (1.33, 901.85)*	29.40 (3.82, 226.56)***	185.24 (18.43, 1861.77)***
KL Distance	3.78 (1.20, 11.95)*	4.54 (1.00, 20.49)*	1.95 (0.47, 8.10)	5.24 (0.58, 47.07)

95% Confidence Interval in Bracket

*	P ≤ 0.05
**	P ≤ 0.01
***	P ≤ 0.001

Table 3.4 Paired Patients' Probabilities TTest P-Value between Own and Coworkers

	Table 4: Paried Patients' Probabilities Ttest P-Value between Own and Coworkers*	
	Own Compared to Co-worker before Move	Own Compared to Coworker after Move
Probability of Prostatectomy	P= 0.47	P= 0.28
Probability of IMRT	P=0.76	P= 0.39
Probability of AS and None	P= 0.03	P= 0.22
Average Entropy Scores of Patients	P= 0.66	P=0.39
*: None Hypothesis is Difference of Mean Equals to 0; Ha is two sided		

Chapter 4

Table 4.1 Inpatient Input Price Index and Medicare Economic Index

Table 1: Inpatient Input Price Index and Medicare Economic Index			
	Inpatient Input Price Index	Medicare Economic Index (MEI)	
2005*	4.20%	2.30%	
2006*	3.90%	1.80%	
2007	3.40%	2.10%	
2008	3.40%	1.80%	
2009	3.20%	1.60%	
2010	2.20%	1.20%	
2011	2.70%	0.40%	
2012	2.90%	0.60%	
2013	2.60%	0.80%	
2014	2.60%	0.80%	
2015	2.80%	0.80%	
2016	2.50%	1.10%	

Note*: Inpatient Input Price Index of 2005 and 2006 are from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareProgramRatesStats/MarketBasketData
Inpatient Input Price Index of 2007 to 2016 are from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/TR2017.pdf
MEI of 2005 and 2006 are from are from https://www.cms.gov/Regulations-and-Guidance/Guidance/FACA/Downloads/MEI-Review-Report-to-HHS.pdf
MEI of 2007 to 2016 are from https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/TR2017.pdf

Table 4.2 Average Cost for Different Treatments

Table 2: Average Cost for Different Treatment

Year	Prostatecotomy	Robotic	IMRT	Conformal3D	Brachytherapy	Proton	Stereotactic	ADT	Cryotherapy	AS
2004	18632.29 (9364.373)	18627.31 (9446.756)	31422.32 (7092.124)	18905.97 (6826.453)	16469.05 (7755.005)	31041.79 (5686.667)	24840.54 (14274.4)	9916.323 (8287.374)	8968.781 (5340.743)	2942.68 (6042.538)
2005	18466.13 (10109.01)	18655.78 (8954.31)	31224.82 (7013.713)	19144.01 (7004.946)	16959.85 (9018.943)	32594.47 (5772.244)	27302.38 (369.9463)	10358.86 (9898.38)	9547.031 (6342.465)	3086.565 (6769.327)
2006	19577.22 (10763.68)	19093.44 (9348.159)	31098.91 (6798.788)	19801.63 (7373.35)	17742.23 (10289.07)	33776.81 (7809.3)	26464.16 (5666.457)	11018.89 (10996.61)	8843.735 (5853.44)	3329.112 (7003.936)
2007	18163.68 (10292.99)	18636.8 (9398.008)	30139.62 (6280.854)	20317.46 (7143.737)	17809.81 (10385.32)	37525.01 (3037.059)	24546.19 (6406.434)	10632.83 (10800.69)	8308.347 (6265.419)	3437.086 (7181.06)
2008	19104.35 (10374.9)	19120.99 (9746.096)	29462.42 (6515.375)	20791.34 (7489.732)	18179.86 (10649.83)	37491.61 (3711.423)	23464.73 (6100.054)	11094.76 (11510.44)	9640.55 (6456.01)	3655.236 (7338.011)
2009	19802.36 (11030.43)	19723.23 (10476.31)	30032.73 (5941.764)	20670.22 (7638.383)	17856.75 (10431.44)	33997.08 (7863.232)	22185.85 (5962.737)	11147.35 (11274.86)	9806.885 (6169.112)	3671.779 (7520.678)
2010	19608.07 (11156.73)	20178.81 (10464.28)	30278.33 (6272.475)	22328.57 (7315.04)	18218.62 (10915.09)	39985.06 (4517.883)	21959.41 (5785.742)	11305.18 (11798.44)	10592.19 (7083.429)	3694.761 (7415.902)
2011	18580.3 (10130.54)	19556.22 (10217.59)	30505.7 (5987.084)	22204.75 (8965.414)	19257.72 (11318.75)	41310.77 (7401.165)	21496.06 (7125.538)	11489.06 (11589.38)	10653.27 (6166.173)	3328.799 (7328.763)
2012	20292.52 (12785.67)	20054.86 (10646.54)	27079.72 (6460.289)	22868.09 (9116.412)	19890.45 (11229.41)	39174.25 (7285.683)	19792.87 (7166.009)	11643.21 (12404.16)	10149.59 (6484.982)	2594.477 (6412.759)
2013	18846.63 (10798.87)	19916.26 (10639.65)	22895.55 (8871.226)	22909.05 (8539.667)	19154.64 (10377.06)	37989.93 (9100.935)	17996.9 (5526.431)	12252.49 (11905.41)	9566.288 (5624.675)	2747.113 (6586.452)
2014	18391.02 (11094.96)	20268.14 (10744.06)	24170.99 (8636.526)	22119.32 (9477.135)	18839.52 (10475.52)	39001.24 (8995.723)	16933.01 (6297.578)	11578.93 (11616.37)	8500.414 (4083.805)	2923.073 (6560.864)
2015	18324.31 (12065.59)	18706.71 (10955.33)	26760.44 (5345.86)	23359.73 (8774.008)	19624.47 (11985.59)	40178.79 (8111.073)	16829 (7361.49)	12728.8 (12372.24)	9317.669 (6810.249)	2895.17 (6194.89)

Standard Deviation in the parentheses

Table 4.3 Average Reimbursement Change and Patients' Volume Change by Year at Urologists Level

Table 3: Average Reimbursement Change and Patients' Volume Change by Year at Urologist Level		
	Average Reimbursement Change in 2016 USD Value	Actual Average Patients' Volume Change
2005 Compare to 2004	-518.16	-0.3
2006 Compare to 2005	-177.36	0.2
2007 Compare to 2006	-1,036.41	-0.2
2008 Compare to 2007	-521.41	-0.9
2009 Compare to 2008	-365.11	-0.6
2010 Compare to 2009	-20.49	-0.6
2011 Compare to 2010	-586.32	0.1
2012 Compare to 2011	-1,342.31	-1.9
2013 Compare to 2012	-1,569.22	0.7
2014 Compare to 2013	268.37	-0.6
2015 Compare to 2014	246.27	1.0

Table 4.4 Active Surveillance Treatment Number and Percentage by Year

Table 4: Active Surveillance Treatment Number and Percentage by Year			
	Number of Patients Undertaking Active Surveillance	**Total Number of Patients in Sample**	**Percentage**
2005	1,919	9,049	21.21%
2006	2,014	9,677	20.81%
2007	2,124	10,008	21.22%
2008	2,225	9,690	22.96%
2009	2,127	8,955	23.75%
2010	2,074	8,407	24.67%
2011	2,197	8,268	26.57%
2012	1,752	6,281	27.89%
2013	1,857	6,165	30.12%
2014	1,812	5,844	31.01%
2015	1,826	5,804	31.46%
Total	21,927	88,148	24.88%

Table 4.5 Number of Urologists and Number of Patients Treated by Different Urologist Types

	Table 5: Number of urologists and Number of Patients treated by Urologist Type					
	Number of Urologists			Number of Patients Treated by Urologists Type		
Year	Surgery Urologist	IMRT Urologist	All Other	Surgery Urologist	IMRT Urologist	All Other
2005	68 (9.47%)	84 (11.69%)	566 (78.83%)	823 (9.09%)	1023 (11.31%)	7203 (79.6%)
2006	76 (10.25%)	124 (16.73%)	541 (73%)	897 (9.27%)	1636 (16.91%)	7144 (73.82%)
2007	94 (11.35%)	154 (18.59%)	580 (70.04%)	1201 (12%)	1972 (19.7%)	6835 (68.3%)
2008	100 (12.03%)	187 (22.5%)	544 (65.46%)	1168 (12.05%)	2139 (12.05%)	6383 (65.87%)
2009	113 (13.61%)	227 (27.34%)	490 (59.03%)	1210 (13.51%)	2536 (28.32%)	5209 (58.17%)
2010	114 (13.81%)	236 (28.6%)	475 (57.57%)	1233 (14.67%)	2431 (28.92%)	4743 (56.42%)
2011	109 (13.32%)	243 (29.7%)	466 (56.96%)	1088 (13.16%)	2582 (31.23%)	4598 (55.61%)
2012	114 (14.48%)	216 (27.44%)	457 (58.06%)	904 (14.39%)	1868 (29.74%)	3509 (55.87%)
2013	106 (13.62%)	221 (28.4%)	451 (57.96%)	880 (14.27%)	1765 (28.63%)	3520 (57.1%)
2014	86 (11.39%)	225 (29.8%)	444 (58.8%)	659 (11.28%)	1825 (31.23%)	3360 (57.49%)
2015	95 (13.19%)	185 (25.69%)	440 (61.11%)	715 (12.32%)	1549 (26.69%)	3540 (60.99%)

Supplementary Files

Chapter 2

Supplementary Table 1: Coefficients, Standard errors, and P-value of Formula 4

	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	-2.41985469	0.09192654	-26.3237882	1.024618e-152
Probability of Active Surveillance	3.58153480	0.04959501	72.2156256	0.000000e+00
Entropy Score	0.31477660	0.03948597	7.9718602	1.563035e-15
Teaching	-0.02164460	0.02170968	-0.9970026	3.187633e-01
Peer KL Distance	0.52726339	0.10932800	4.8227664	1.415807e-06
HSA Level HHI	-0.39495124	0.11552622	-3.4187152	6.291753e-04
Network Group Medium Compared to Low	0.03162707	0.02687446	1.1768451	2.392574e-01
Network Group High Compared to Low	0.09017647	0.02789747	3.2324253	1.227442e-03

Chapter 4

Supplementary 4.1

For prostatectomy treatment, I included the claims from physicians' services (NCH), Outpatient (Outsaf), and hospital cares (Medpar). For the claims of hospital cares, I included the "Amount of payment made from the Medicare trust fund for the services covered by the claim record", the "The amount of money identified as the beneficiary's liability for Inpatient deductible for the stay", "The amount of money identified as the beneficiary's liability for part A coinsurance for the stay", "The amount of additional payment made to teaching hospitals for IME for the stay", "The amount paid over the DRG amount for the disproportionate share hospital for the stay", and "The amount of additional payment approved due to an outlier situation over the DRG allowance for the stay". For the claims in Outpatient, I included payment "Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim", and payment "Made on behalf of Beneficiary by a primary payer other than Medicare". For the claims of physician's services, I included payment

“Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim”, and payment “Made on behalf of Beneficiary by a primary payer other than Medicare”.

For IMRT Treatment, I included the claims from physicians’ visits (NCH), and Outpatient (Outsaf). For both physicians’ visits and Outpatient, I included payment “Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim”, and payment “Made on behalf of Beneficiary by a primary payer other than Medicare”.

For Active Surveillance, I included claims from physicians’ services (NCH) and Outpatient (Outsaf). For claims from physicians’ services (NCH), I included payment “Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim”, payment “Made on behalf of Beneficiary by a primary payer other than Medicare”, and “The amount of the cash deductible as submitted on the claim”. For the claims from Outpatient (Outsaf), I included payment “Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim”, payment “Made on behalf of Beneficiary by a primary payer other than Medicare”, “The amount of the cash deductible as submitted on the claim”, and “Beneficiary’s liability for Part B coinsurance as determined by intermediary”.

For Other Treatments, I included the claims from physicians’ services (NCH), and Outpatient (Outsaf). For both physicians’ services and Outpatient, I included payment “Made to Provider and/or Beneficiary from trust fund (after deductible and coinsurance amounts) for services covered by Institutional claim”, and payment “Made on behalf of Beneficiary by a primary payer other than Medicare”.

Supplementary Table 2: Coefficients, Standard errors, and 95% Confidence Intervals of Formula 5

AS4	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
probASNonegrp40415	1.045881	.0088546	118.12	0.000	1.028525	1.063236
Entrotr	-.0025584	.0058434	-0.44	0.662	-.0140116	.0088948
EXPACTcurrentnor	.0150027	.0064756	2.32	0.021	.0023105	.0276949
estivoldiffcurrent	.0001627	.0006864	0.24	0.813	-.0011826	.0015079
teachingcurrent						
2	-.0128469	.0093642	-1.37	0.170	-.0312008	.005507
9	-.0109243	.0163729	-0.67	0.505	-.0430154	.0211668
1.IMRTcap	-.016885	.0113527	-1.49	0.137	-.0391364	.0053664
yeardiag						
2006	-.0024931	.0068602	-0.36	0.716	-.0159393	.0109531
2007	-.0001528	.0069673	-0.02	0.983	-.0138087	.0135032
2008	.0025863	.0072617	0.36	0.722	-.0116466	.0168192
2009	.007206	.0075926	0.95	0.343	-.0076757	.0220877
2010	.0027815	.0080965	0.34	0.731	-.0130877	.0186507
2011	.012455	.008465	1.47	0.141	-.0041364	.0290464
2012	.0171021	.0097867	1.75	0.081	-.00208	.0362841
2013	.0208604	.0107669	1.94	0.053	-.0002428	.0419637
2014	.0064362	.0110352	0.58	0.560	-.0151929	.0280653
2015	.0080758	.0110644	0.73	0.465	-.0136105	.0297621
_cons	-.0299545	.0090676	-3.30	0.001	-.0477272	-.0121819
sigma_u	.1091724					
sigma_e	.3682305					
rho	.08079741	(fraction of variance due to u_i)				

F test that all u_i=0: F(759, 47829) = 3.85 Prob > F = 0.0000

Supplementary Table 3: Coefficients, Standard errors, and 95% Confidence Intervals of Formula 6

AS4	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
probASNonegrp40415	1.040738	.0088491	117.61	0.000	1.023393	1.058082
Entrotr	-.0042522	.0058718	-0.72	0.469	-.0157611	.0072567
typecurrentnum						
2	-.031636	.0089823	-3.52	0.000	-.0492415	-.0140305
3	.0460466	.0077212	5.96	0.000	.030913	.0611802
EXPACTcurrentnor	.0396025	.0175742	2.25	0.024	.0051568	.0740482
typecurrentnum#c.EXPACTcurrentnor						
2	-.041535	.0207545	-2.00	0.045	-.0822142	-.0008559
3	-.0296165	.0186629	-1.59	0.113	-.0661961	.006963
estivoldiffcurrent	-.0011004	.0016172	-0.68	0.496	-.0042702	.0020694
typecurrentnum#c.estivoldiffcurrent						
2	-.0001715	.0021088	-0.08	0.935	-.0043047	.0039617
3	.0016079	.0017537	0.92	0.359	-.0018293	.0050452
teachingcurrent						
2	-.0122033	.0093736	-1.30	0.193	-.0305757	.0061691
9	-.0183613	.0163681	-1.12	0.262	-.0504431	.0137205
1.IMRTcap	-.0027564	.011409	-0.24	0.809	-.0251182	.0196055
yeardiag						
2006	.0026232	.0068678	0.38	0.702	-.0108378	.0160843
2007	.0077281	.0069997	1.10	0.270	-.0059914	.0214475
2008	.0102578	.0072858	1.41	0.159	-.0040225	.0245381
2009	.0223289	.0076686	2.91	0.004	.0072984	.0373595
2010	.0182483	.0081719	2.23	0.026	.0022313	.0342653
2011	.0306557	.0085558	3.58	0.000	.0138862	.0474253
2012	.0334296	.0098479	3.39	0.001	.0141277	.0527316
2013	.0351803	.0108107	3.25	0.001	.0139912	.0563694
2014	.0247617	.0111057	2.23	0.026	.0029943	.0465291
2015	.0248281	.0111192	2.23	0.026	.0030342	.0466219
_cons	-.0624941	.0110751	-5.64	0.000	-.0842015	-.0407866
sigma_u	.10555578					
sigma_e	.36752181					
rho	.07620337	(fraction of variance due to u_i)				

F test that all u_i=0: F(759, 47823) = 3.61 Prob > F = 0.0000

Supplementary Table 4: Coefficients, Standard errors, and 95% Confidence Intervals of Formula 7

AS4	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
probASNonegrp40415	1.063968	.0104352	101.96	0.000	1.043515	1.084422
Entrotr	-.0008186	.0065539	-0.12	0.901	-.0136645	.0120273
NPISurgKL						
2	-.0081426	.0059062	-1.38	0.168	-.0197188	.0034337
3	-.0275016	.0061797	-4.45	0.000	-.039614	-.0153892
EXPACTcurrentnor	.0290757	.0153471	1.89	0.058	-.0010051	.0591565
NPISurgKL#c.EXPACTcurrentnor						
2	.0200097	.0153997	1.30	0.194	-.0101742	.0501936
3	-.0020169	.0164449	-0.12	0.902	-.0342495	.0302157
NPIIMRTKL						
2	-.0097316	.007058	-1.38	0.168	-.0235654	.0041023
3	-.0350547	.00757	-4.63	0.000	-.0498921	-.0202174
EXPACTcurrentnor	0	(omitted)				
NPIIMRTKL#c.EXPACTcurrentnor						
2	-.0183666	.0168929	-1.09	0.277	-.0514773	.014744
3	-.0310809	.0174434	-1.78	0.075	-.0652705	.0031087
estivoldiffcurrent	.00022	.0008147	0.27	0.787	-.0013769	.0018169
teachingcurrent						
2	-.0188135	.010795	-1.74	0.081	-.0399721	.0023451
9	-.0167901	.0203647	-0.82	0.410	-.0567055	.0231253
1.IMRTcap	-.0002849	.014323	-0.02	0.984	-.0283585	.0277887
yeardiag						
2006	.0088408	.008883	1.00	0.320	-.0085701	.0262517
2007	.0105151	.009153	1.15	0.251	-.0074251	.0284553
2008	.0110901	.0094817	1.17	0.242	-.0074943	.0296745
2009	.0151978	.0097415	1.56	0.119	-.003896	.0342916
2010	.008838	.0101997	0.87	0.386	-.0111537	.0288297
2011	.0168608	.0105853	1.59	0.111	-.0038868	.0376085
2012	.0072263	.0124337	0.58	0.561	-.0171442	.0315969
2013	.0201378	.0130087	1.55	0.122	-.0053597	.0456353
2014	.006585	.0134033	0.49	0.623	-.019686	.0328559
2015	.0084462	.0129334	0.65	0.514	-.0169036	.0337961
_cons	-.0112215	.0122684	-0.91	0.360	-.035268	.0128249
sigma_u	.10894182					
sigma_e	.36442897					
rho	.08203334	(fraction of variance due to u_i)				

F test that all u_i=0: F(668, 34003) = 3.04 Prob > F = 0.0000