ANALYSES OF PHYSICIAN LABOR SUPPLY DYNAMICS AND ITS EFFECT ON PATIENT WELFARE

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ABSTRACT

Jing Teresa Zhou: Analyses of Physician Labor Supply Dynamics and its Effect on Patient Welfare
(Under the direction of Donna Gilleskie)

My dissertation focuses on the supply side of health and labor economics in order to inform policymakers who seek to address physician shortages and thus improve patient welfare in the United States.

The first chapter evaluates the determinants of physician geographic and professional movement within North Carolina (NC) using a dynamic discrete choice model designed to analyze labor supply behaviors of individuals over time. I jointly model the initial specialty, activity, location, facility, and hours of direct patient care of all physicians in NC from 2003 to 2012 using a full information maximum likelihood estimation approach that allows for correlation of unobserved determinants. Using the parameter estimates from the dynamic model, I simulate several policy interventions aimed to attract and retain physicians in rural and underserved areas. I find that loan forgiveness policies are less effective at decreasing the probability of movement and increasing retention in the same rural county than an increase in the reimbursement rate. An increase in midlevel practitioners decreases retention in rural areas and increases the likelihood of a physician becoming inactive, while an increase in registered nurses in rural areas significantly increases physician retention.

The second chapter evaluates the relationship between physician supply and patient welfare. Ambulatory care sensitive conditions (ACSC) are preventable or manageable with access to a primary care physician (PCP) and medication, but progression of ACSC tends to lead to costly hospitalizations. Results from existing literature on the causal effect of PCP supply on ACSC admissions are mixed. These mixed results can be explained by the endogeneity issue (i.e., the explanatory variable is correlated with the error term) that arise from simultaneous causality and omitted variables bias. This chapter addresses the endogeneity problem in the literature and correctly identify the true effect of PCP supply on patient welfare by using exogenous policies related to Health Professional Shortage Area (HPSA) designation at the county level. Using data from NC and Regression Discontinuity (RD) design, I find that a decrease in PCP supply leads to a significant increase in the number of the ACSC admissions, and vice versa.

To my parents, Dr. Hong Zhou and Ms. Ning Liu, whose love, selfless support and passion for learning laid the foundation for the discipline and application necessary to complete this work.

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CHAPTER 1

INTRODUCTION

The Gross Domestic Product (GDP) of the United States in 2014 was around 17.4 trillion dollars, almost 7 trillion dollars more than the second largest economy. Perhaps even more mind-boggling is the fact that one out of every six dollars spent in the US that year is spent on health care (i.e., 17 percent of GDP went toward national health expenditures, NHE, compared to the 10 percent world average), in the form of physician office visits, surgeries, medicines, and new investments in medical research.[1] In the US, twenty percent of total NHE constitutes physician and clinical services, which is the second largest category after hospital care (32%).[2] In addition to its substantial monetary cost, adequate physician presence is essential to patient welfare. However, undersupply of physicians is a pressing health issue in the US and around the world. Concern exists among the public that a continuing physician shortage will drive up medical care costs, increase waiting times, shorten office visits and, generally, decrease overall patient welfare.[3] A significant amount of research has shown that, instead of an aggregate shortage, there is a maldistribution of physicians both geographically and by specialty in the US. Existing physician supply models challenge our ability to understand incentives, with the objective of promoting equity of access, since they do not consider in detail the physician and location characteristics that affect physician location decisions. Multiple programs (federal and state) have been created to increase physician supply to meet physician shortages. However, these programs have had limited success at maintaining physician presence in underserved areas.

My dissertation addresses the supply side of the health care market using both economic theory and empirical strategies in the form of two stand-alone papers in the following chapters. My first paper (Chapter 2) focuses on building a holistic physician supply model captures the employment behavior of physicians in the US. Existing physician supply models challenge our ability to understand incentives, with the objective of promoting equity of access, since they do not consider in detail the physician and location characteristics that affect physician

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[1]Health expenditure, total (% of GDP): World Health Organization Global Health Expenditure database, The World Bank.

[2]National Health Expenditure Data, 2014: Centers for Medicare & Medicaid Services, Office of the Actuary, National Health Statistics Group.

[3]Smith, Yolanda. Physician Shortage. News-Medical.net, 30 June 2016, www.news-medical.net/health/Physician-Shortage.aspx.

location decisions. My paper evaluates the determinants of physician geographic and professional movement within North Carolina (NC) using dynamic empirical models designed to analyze the behavior of individuals over time. I jointly model specialty, practice location, facility type, and hours worked of all physicians in NC from 2003-2012. I also study the determinants of physician movement within NC by race and ethnicity, which has not been studied in detail. In order to address these questions, I collected physician data from the NC medical board, which tracks all physician movement across NC. I obtained the physician licensures of all board-certified physicians in NC from 2003-2012 and used the information to construct a database that includes physician demographics, specialty, location of practice, facility type, and hours worked for each year an individual physician practices in NC over this period. I have also merged the physician-level information with county-level information from Log into NC (LINC), and with constructed salary variables from the Hospital and Healthcare Compensation Service (HHCS) and NC Occupational Employment Statistics (OES).

Using the model I built, my research informs policies aimed to attract more physicians to underserved communities and to maintain their presence in order to achieve equity of health care access in the US. However, in reality, there has not been an amelioration of this problem due to the low retention of physicians in underserved areas. In this paper, I find programs that forgive medical school debt if a physician serves in a rural area is less effective at retaining physicians in rural areas than an increase in reimbursement rates, which increases the physicians salary. In another words, loan forgiveness programs are a short-term solution to a long-term problem. I also find a change in other medical care providers or support staff also affects physician behavior, where mid-level practitioners (i.e., physician assistants, advance nurse practitioners) decrease retention and increase physician transition to inactivity-and are thus a substitute for physicians- while an increase in Registered Nurses (or RNs), a complement to physicians, significantly increases retention in rural areas.

In my second paper (Chapter 3), I shift my attention to evaluate the effect of physician presence on patient welfare. The question remains that whether an increase of physician supply from federal and state policies improves health of the population in the long run. I use the same dataset of physicians and county characteristics I built from the aforementioned chapter and combined it with all hospital discharges in NC to evaluate the effect of the number of primary care physicians on preventable hospital admissions, or Ambulatory Care Sensitive Conditions (ACSC), in NC. Because existing studies provide mixed results on the subject, I use the Regression Discontinuity (RD) design, to correct the statistical deficiencies in the literature. I find that an increase in the supply of primary care physicians (PCP) significantly decreases hospital admissions for preventable ailments. From a cost-benefit analysis, a increase in the number of PCP in underserved areas is more beneficial to patient welfare, because it is less expansive to treat preventable ailments with regular visits to primary care physicians than waiting for acute manifestations of these ailments that results in hospital admissions.

The combined analyses and results from the two chapters address the mechanisms that impact the physician labor force and the effect of physicians on patient welfare through rigorous econometric methods. My dissertation improves upon existing models in both health economics and health policy by evaluating a wide range of factors that influence physician geographic and professional movement as well as uncovering the beneficial effect of access to physicians on patient health.

CHAPTER 2

THE DOCTOR IS IN/OUT: DETERMINANTS OF PHYSICIAN LABOR SUPPLY DYNAMICS

2.1 Introduction

Two concerns about physician labor supply dominate the academic literature and the popular press: shortage and maldistribution. The American Medical Association (AMA) contends that their data, used by the US Department of Health and Human Services (USDHHS) to calibrate physician workforce models, uncover significant current and anticipated shortages.[1] Other researchers (Zurn, 2004; Dussualt, 2006; and Dorsey, 2011) argue that there exists a maldistribution of physicians both geographically and by specialty, which leads to a shortage of certain types of doctors in some areas and a surplus in other areas. Indeed, a frequent observation about physicians is the clustering of specialists in metropolitan areas and a shortage of physicians in rural areas. Some argue that an important contributor to this uneven distribution is financial barriers that prevent individuals who would be the most likely to serve in primary care and in underserved areas from entering the profession (Vaughn, et al., 2010; Dorsey et al., 2011). Others emphasize that physicians tend to be attracted to areas with complementary staff in order to practice effectively (Stange, 2003; Roblin et al., 2004; MGMA, 2016). Others argue that current health care system regulations that require a substantial amount of documentation by physicians have reduced the time available for direct patient care and could potentially increase burn out (Christino, et al., 2017). Efforts to mitigate these concerns require an understanding of determinants of physician labor supply decisions regarding specialty, geographic location, facility type, hours worked and continued practice over one's career.

Current leading models of physician supply, developed by the AMA, USDHHS and American Association of Medical Colleges (AAMC), aggregate physician behavior to the national or state level, while ignoring individual preferences shaped by gender, race, and experience as well as within-state variations in physician demand, supply conditions, and location amenities. A recently-developed interactive tool, the FutureDoc Forecast Tool,

[1] Shortage, in this context, does not embody the full characterization used by economists, which suggests that demand exceeds supply due to pricing irregularities in the labor market (i.e., in a competitive market, wages should adjust to equate supply and demand). The AMA, USDHHS and other medical organizations use the term physician shortage to describe a situation in which there are not enough physicians to treat all patients in need of medical care. Thus, policy recommendations are targeted toward training and retention of physicians.

improves upon the three models by allowing some physician mobility and disaggregation to the county level.[2] The forecasting model, which uses inventory projections from historical data on separation and arrival rates, does not attempt to explain what drives observed physician employment behaviors.

I formulate and estimate a dynamic model of physician behaviors that includes initial specialty, activity (whether or not to remain active), location, facility, and hours of direct patient care. I use the population of licensed physicians in North Carolina (NC) over 10 years (2003-2012) to explore the underlying factors that explain the professional behaviors of physicians. An economic model of mobility decision-making motivates a set of estimable, correlated, and dynamic labor supply equations whose probabilities or densities form the likelihood of observed physician employment outcomes in the research sample. In addition to individual-level explanatory variables such as gender, race, and age, time-varying county-level characteristics that capture location-specific quality of life, number of physician substitutes or complements (i.e., advanced nurse practitioners, physician assistants and registered nurses) and potential demand shifters help identify endogenous individual behaviors over time. The endogenous histories of behaviors (i.e., work experience, lagged hours worked, facility choices, etc.) also explain current behaviors. I use the estimated data-generating process to simulate the effects of potential policies likely to affect physician migration patterns such as loan forgiveness, increases in service reimbursement rates, midlevel practitioner or registered nurse growth, and changes in Medicare/Medicaid coverage.

To simulate the existing loan forgiveness programs that aim to attract and retain physicians in rural areas, I allow for a lump sum wage increase of $200,000 for all rural physicians in one year. Although the simulated policy is the most generous version of the loan forgiveness program, I find that it does not significantly decrease the average likelihood of movement nor does it decrease the probability of moving one or two years of service in a rural area (i.e., retention). However, an increase in the reimbursement rate in rural counties via a proportional increase in average salary has the potential to increase physician retention in rural areas. A 5-percent increase in rural county salaries decreases the probability of moving after one year by 11.7 percent and moving after two years by 6.7 percent. Male physicians are more responsive to the policy change than female physicians and, for both groups, there is a decreasing marginal return to a larger increase (10 or 20 percent) in salary. Other policies that impact physician movement and retention involve changing the composition of other medical care professionals. A 5-percent increase in midlevel practitioners in rural counties increases the probability of moving after one or two years by 15.7 percent and 8.3 percent, respectively. The policy also significantly increases the likelihood of a physician exiting the labor force by becoming inactive. A 5-percent increase in

[2]This statistical model and forecasting tool was developed by researchers at the Cecil G. Sheps Center for Health Servcies Research at the University of North Carolina at Chapel Hill and funded by The Physicians Foundation. https://www2.shepscenter.unc.edu/workforce/

RNs in rural counties significantly decrease the probability of leaving after one year and two years of service by 13.8 percent and 2.7 percent, respectively. These findings offer a new understanding of the effectiveness of policies that attempt to change physician behavior and increase retention in rural and underserved areas.

In the next section, I review the relevant literature regarding physician labor supply. Section 3 describes data from the North Carolina Board of Medicine, Log into NC and the Physician Compensation Survey and details construction of the research sample. Section 4 presents a theoretical discrete choice framework that motivates the empirical model detailed in Section 5. Results are presented and discussed in Section 6. Section 7 concludes and provides a discussion of future research.

2.2 Literature Review

Leading physician supply models in the policy research literature simplify physician employment behavior by ignoring many physician characteristics such as race and experience as well as detailed location characteristics. Most of the existing models also aggregate physician labor supply to the national or state level by estimating the historical probability of physician inflow and outflow, while disregarding physician preferences and within-state variations. For example, the most commonly used Physician Supply Model (PSM) developed by the AMA and USDHHS is an inventory model that tracks the supply of physicians by age, gender, country of medical education, type of degree and medical specialty. The model uses historical data to determine the probability that physicians will remain active from year to year and the annual number of hours worked in patient care at the national level. The model takes the number of physicians at time t (starting with the base year 2000), adds in new additions to the physician labor force (i.e., new US medical graduates and international medical graduates) and subtracts attrition each year (due to retirement, death, and disability), arriving at the physician supply for year $t + 1$. The extrapolation of the supply of physicians and hours worked is assumed to be linear in the probability of retirement or death, the probability of being accepted into medical school, graduation from medical school, and other probabilities based on age, gender and specialty. The PSM does not address the heavy presence of physicians in metropolitan areas and severe shortages in rural or poor areas, does not consider movement at the state or county levels, and does not include other individual characteristics such as race or exogenous location-specific amenities or medical market characteristics.

Moving beyond the projections of the PSM models, the health economics literature also compares and contrasts employment behavior by physician characteristics. Panel data analysis of Canadian generalists finds that there is little impact of age on hours worked (Crossley, Hurley, and Jeon, 2009). It also verifies that female physicians work significantly fewer hours on average than male physicians but the aggregate decline in hours of direct patient care from the 1980s through the mid-1990s is not differentially explained by decreases in hours worked over all age or gender groups. Similar results are found for US physician supply (Weisman et al.,1980; Fossett, et al., 1990). Female physicians tend to have higher retirement rates and to work fewer hours in direct patient care, and female physicians are concentrated in pediatrics and psychiatry and are underrepresented in general surgery and other medical subspecialties (Kletke et al., 1990). Although there is a growing representation of female physicians in the labor force, the supply of physicians continues to reflect differential selection of specialty by gender.

The economics literature on labor mobility highlights the role of individual preferences for location characteristics. Although higher (lower) wages and better (worse) economic opportunities are often credited as the major factors that induce general migration into (out of) an area (Muth, 1971; Olvey, 1972; Greenwood, 1985; Partridge and Rickman, 2006), studies have shown the importance of location-specific amenities and positive quality of life measures as drivers of general migration (Cushing, 1987; McGranahan, 1999; Green, 2001; Deller et al., 2001; Cebula and Payne, 2005; Gunderson and Ng, 2006). In seminal work by Roback (1982), the author claims that better amenities would drive down wages and drive up rents, but individuals would rather trade off higher wages and pay higher rents to live in those communities. Building on the same principle, Blanchflower and Oswald (1994, 1995) incorporate Smith's (1985) compensating differential and extend the Roback model in the presence of unemployment. These papers assume free mobility of labor because when migration is costly, workers are more likely to view the decision to migrate as an investment. However, Clark et al. (2003) find that when there are both pecuniary and psychic costs associated with moving, households are generally more responsive to undercompensation between income and location characteristics than overcompensation (i.e., the household perceives a higher opportunity cost of not moving than moving, conditional on the compensation level at the destination and at the origin being the same). These theories tell us that, for an agent with a high wage, there exists a high marginal cost of living in a location with relatively low amenities because, for that person, the marginal benefit of having better amenities is high. Therefore, the agent is more likely to move to an area with relatively higher amenities and lower wages.

In addition to the amenity and wage trade-off literature, a number of studies find that high-income individuals have small or negligible labor supply elasticity with regard to earnings (Pencavel, 1986; Roed and Strom, 2002). Showalter and Thurston (1997) extend their research on white-collar professional labor market decisions to US physicians and focus on tax effects. They find that self-employed physicians are sensitive to marginal tax rate changes, but the effect is small and insignificant for employed physicians. Since physicians are some of the most highly paid professionals in the US,[3] the literature hypothesizes that they are more likely to accept a decrease in

[3]According to the US Census and Bureau of Labor Statistics (BLS), the annual real median personal income is $31,099 in 2016 and the

income for better amenities and the earnings elasticity of labor supply is small.

Recent empirical economic studies use dynamic panel data models and structural discrete choice models to study labor supply (Rizzo and Blumental, 1994; Scott, 2000; Saether, 2005; Baltagi et al., 2005; Cheng et al., 2013; Wang and Sweetman, 2013; Kalb et al., 2015; Andreassen et al., 2013; Broadway et al., 2017). Rizzo and Blumental (1994) evaluate the effects of both income and non-labor income on US physician labor supply among self-employed physicians. They find that the income effect of an earnings change for male physicians is negative. Controlling for the income effect, a one percent increase in wages leads to a 0.49 increase in labor supply. Using Norwegian hospital data between 1993-1997, Baltigi et al. (2005) find labor supply elasticities are around 0.3, but they do not control for physicians heterogeneity across specialties. Saether (2005) uses a static random utility labor supply model and finds that a wage increase causes a small response in total hours and reallocation of hours within the sectors with increased wages. Broadway et al. (2017) estimate a structural, discrete choice model of labor supply and after-hour care (AHC) in a sample of Australian general practitioners. They find that physicians are more likely to increase after-hour care if their daytime-weekday hourly earnings increases, but the effect is very small. Yet, in another setting, hourly wage increases actually reduce the probability of providing AHC, especially among male physicians. The results lead them to conclude that wage increases appear to be, at best, relatively ineffective in incentivizing increased provision of AHC and may even prove harmful if incentives are not well targeted. None of these studies explicitly consider each of the relevant professional decisions of physicians over time nor do they differentiate behavior by race, gender, facility type, or specialty. In addition, they are unable to measure the short- and long-run effects of potential policies that may dynamically impact behaviors through location and facility changes.

My work contributes to the physician labor supply literature by estimating a dynamic model of physician employment behavior (i.e., initial specialty, annual location, facility type, and hours of direct patient care) that accounts for physician preference shifters (i.e., gender, race, age, experience), location-specific amenities, and medical care market characteristics. The ability to separately identify the importance of these factors and to quantify the heterogeneous impact of these factors on physician employment decisions allows us to evaluate the impact of financial incentives that may vary by individual characteristics. Using the estimated parameters of the dynamic data generating process, I simulate the behavior of physicians over time under different policy scenarios.

annual real mean personal income is $50,756. For US physicians, BLS reports a median annual income of $206,920 and mean annual income of $205,560.

2.3 Data and Summary Statistics

Before presenting an economic model of location decisions and professional behavior of physicians, I begin by describing the data that are available. The specific structures of these data inform and dictate the empirical modeling in important ways. The first section details three sources of data, describes variable construction, and summarizes the variables used in analyses. The second section describes the constructed annual income data and the last section describes the county-level medical care market and local amenity characteristics.

2.3.1 Physician Level Panel Data

The North Carolina Physician Licensure Database from the North Carolina Medical Board provides annual physician-level data from 2003 to 2012. The data are collected and released by the North Carolina Health Professions Data System (HPDS). The database tracks the universe of physician applications for NC medical licenses, which must be renewed annually. It provides a comprehensive view of the physician labor force in the state and allows a researcher to track the movement of all physicians within the state across time.

Prior to May 2009, the state allowed two methods for annual license renewal: paper and electronic. Complicated to process and prone to mistakes, paper applications have been phased out in favor of an electronic renewal process on the NC Medical Board website. Because medical licenses are time delimited, the Board sends a renewal notice two months before each physician's deadline (dated as his/her birthday). On average, the electronic renewal process takes about 15 minutes because the information regarding education history, demographics, and work history often remains unchanged. If a physician changed location of practice, facility type, or specialty, they must update this information. Many physicians also provide updates when they decide to become inactive, by indicating retirement or other reasons. Inactive physicians that annually update their status can avoid a time-consuming reinstatement process should they decide to return to practice.[4]

If a physician fails to renew the license on time, a grace period of 30 days is provided and the physician is charged an additional late fee. If renewal is not completed during the grace period, the license is placed on inactive status and it is illegal to practice medicine or surgery, write prescriptions or administer prescription drugs in NC under any circumstances. If the inactivity period is less than one year, it is necessary to pay an additional fee and undergo a background check to reactivate the license.

However, if there has been an interruption in the continuous, clinical practice of medicine greater than two years, the applicant may have to reestablish his or her competence to practice medicine safely to the Board's

[4]Among physicians who become inactive by notifying the board, rather than failure to renew, the four most common reasons are: primarily engaged in medical research and/or teaching, employment in a non-medical field/industry, temporarily out of the labor force, and retirement.

satisfaction, in accord with GS 90-14 (11a). The reinstatement procedure might entail, and is not limited to, full-scale assessments, engagement in formal training programs, supervised practice arrangements, formal testing (Board Examination), or other proofs of competence. The Board is much more likely to require a physician who has not maintained annual notification of reason for inactivity to undergo these competency procedures.[5] Such decisions are made on a case by case basis.

After a physician submits his/her application, the information is processed and updated in HPDS. Basic information in the database includes an ID number to identify the physician through time (not the board license number), gender, race, age, medical school, internship, residency, location of practice, facility type, and practice specialty.

The data obtained from the Medical Board include 43,765 uniquely-identified physicians or a total of 293,835 person years over the period 2003-2012. These person-year observations include all instances where physicians maintained either active or inactive status in NC; 5,427 physicians are never active in NC and 5,339 physicians appear only once in the sample. I restrict the research sample to the longest spell of continued communication with the Board for each physician. I do not include multiple spells within the observation period of the data because I do not observe a physician's activities between spells and therefore cannot construct relevant variables that explain re-entry into the NC physician labor force. Prior to selection based on the longest spells, person-year observations for which location, facility type or hours worked is missing and cannot be intelligently imputed are considered a break in a spell; 2,518 physicians are missing employment location that cannot be filled in and 573 are missing facility or specialty. The research sample also includes physicians with at least two years of observation in order to model location transitions. With these necessary removals, my research sample contains 29,908 uniquely-identified physicians who contribute two to 10 years of observed practice behaviors, for a total of 187,402 person-year observations. Conditional on being active in NC and having renewed their license by the next period, there are 165,668 person-year observations in the sample.

This rich dataset allows me to explore the professional behavior of physicians practicing in NC. Among those in my research sample, duration of practice in NC is unknown because I do not observe how long a physician has been in the state when first observed in 2003. However, years of experience as a Board-certified physician are available. In the research sample, 19.94 percent of physicians ever report zero years of experience; these are new entrants to the profession who initially locate in NC. Despite the large entry rate, I only observe physicians in NC and cannot explain a physician's decision to locate in NC. Because the attrition rate is small

[5]Updated requirements for medical license renewal process comes from the North Carolina Board of Medicine: http://www.ncmedboard.org/renewals/renewal_type/category/physicians.

(i.e., 2.5 percent move out of NC and 1.7 percent become inactive), I have chosen to focus on the determinants of movement within the state.

Activity and Location

Using the zipcode and its respective FIPS code provided in the data, I define the primary county of practice for each active physician. Location variables (zipcode and county) define physician movement from one year to the next as well as whether the location is rural or urban. Because physicians are not required to provide a residential address, my research cannot differentiate residential location from employment location.

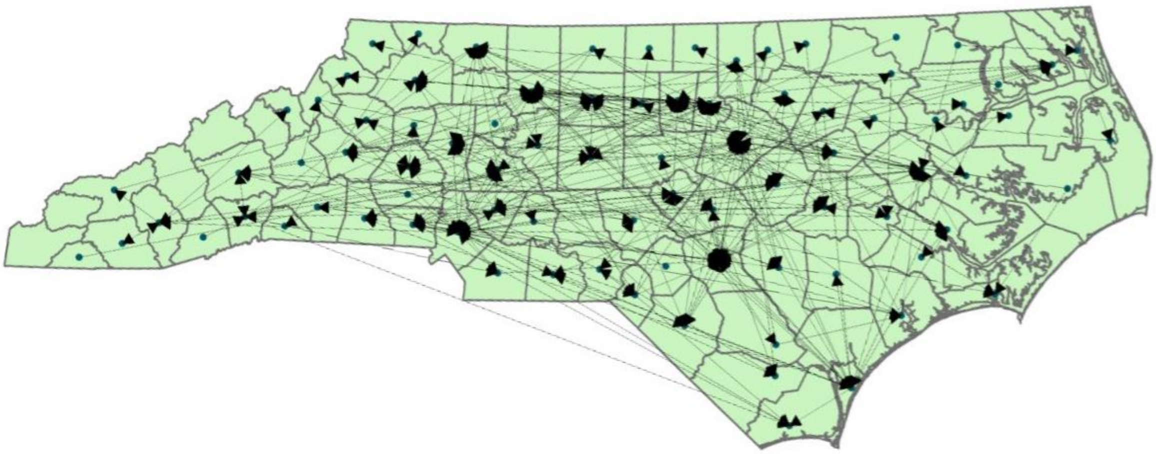
The partial equilibrium model that motivates my empirical analysis considers annual employment location decisions of physicians. An empirical analysis of physician location decisions might consider all zipcodes or metropolitan areas as the relevant set of location alternatives. It is computationally infeasible, however, to allow location alternatives to include each of the 850 zipcodes across the 100 counties in NC. Additionally, consistent time-series data on location amenities are not available over time at the zipcode level. Finally, data on medical care market characteristics are likely to vary at the county level and, generally, may not change at the zipcode level. Hence, efforts are made to reduce the set of location alternatives.

Aggregation from zipcode to county results in 102 location alternatives (i.e., move to any of the 100 counties, move out of NC, or become inactive), which presents too many alternatives for a multinomial logit estimation that also includes unconditional explanatory variables.[6] I examined county-to-county moves to determine whether consideration of adjacent counties only might be a reasonable way to narrow the choice set. To demonstrate the complexity of county-to-county movement, Figure 2.1 shows the origination and destination counties for physicians who moved from 2003 to 2004, with the end destination for each move indicated by a black arrow and the blue dot is the centroid of the county.

To make clear the variety of destinations, Figure 2.2 focuses on movement of physicians from one county (Orange County) in one year (2003-2004). Orange County is one of the most populated counties in NC and contains a large, public research and teaching hospital. In one year, there were 27 physicians who moved from Orange County (denoted by blue lines) and 13 physicians who moved to Orange County from other counties (denoted by red lines). Although physicians may move to neighboring counties, the majority of moves were across the state to non-neighboring counties. Physician movement out of urban Orange County also included both rural and urban destinations (where urban counties are denoted in green and rural counties are denoted in

[6]In the Appendix, I show results from a 102-alternative conditional multinomial logit model with county-level characteristics from all 100 counties and a mixed multinomial logit model with both county-level factors and a few individual-level characteristics. Here, I can allow specifically for both push and pull county level factors to explain location transitions. However, I prefer the model presented in this chapter because it allows me to include more physician characteristics in order to explore heterogeneous effects of location characteristics on movement.

Figure 2.1: Physician Movement within NC, 2003-2004



blue). Table 2.1 shows the average distance (in miles) of moves within NC using centroid to centroid calculation at the county level, where the average distance for all physicians who moved is around 61 miles.

Figure 2.2: Physician Movement to and from Orange County, 2003-2004

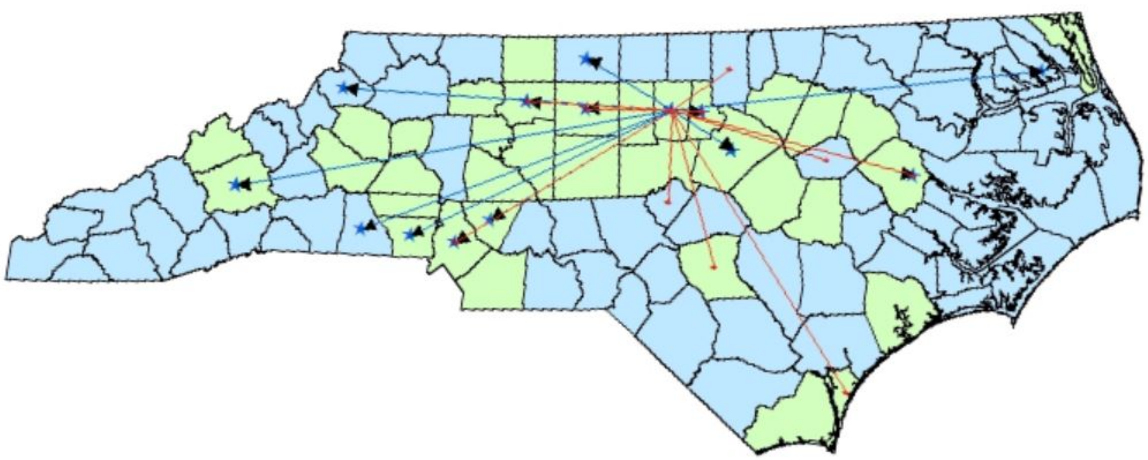


Table 2.1: Summary Statistics: Average Distance of Moves in Miles

Year	Mean	Std	Min	Max	Median	Freq
2004	87.48	63.33	13.72	433.36	74.97	367
2005	63.09	59.35	8.93	378.74	38.09	1241
2006	62.86	60.50	8.93	434.60	37.03	1117
2007	60.84	53.50	12.17	407.36	38.68	729
2008	61.59	57.15	12.17	413.89	38.38	818
2009	59.68	54.77	11.26	373.75	37.31	1062
2010	53.57	50.03	11.26	341.64	33.50	863
2011	61.34	56.58	11.26	384.85	38.68	916
2012	52.56	50.06	8.93	376.61	32.22	1076
Total	60.78	56.38	8.93	434.60	38.09	8189

Note: Statistics are based on 8,189 physicians who moved to a different county within NC in any given year.

To further explore movement, I summarize physician location within NC by urbanicity/rurality of the county and of the zipcode within the county in Table 2.2.[7] Around 73.3 percent of physicians employed in an urban county are in an urban zipcode, while around 14.2 percent of physicians in a rural county are in a rural zipcode.

Table 2.2: Location by Urbanicity/Rurality of County and Zipcode

	Urban Zipcode (%)	Rural Zipcode (%)	Marginals (%)
Urban County (%)	73.26	6.43	79.69
Rural County (%)	6.14	14.17	20.31
Marginals	79.40	20.60	100.00

Note: Statistics are based on 165,668 person-year observations among active physicians including their first year in the sample.

Conditional on being active in NC in a given year, a physician may remain in the same location of employment in NC, move within NC, move out of NC or become inactive in the next year. Table 2.3 shows the activity and location outcomes by year. Over 83 percent of year-to-year observations involve no change in activity or location, 12 percent involve a move within NC and 2.5 percent involve a move out of state, while less than two percent of transitions are to inactivity. A majority of the physicians who changed zipcode of employment moved

[7] I follow the county urbanicity/rurality definition used by the Sheps Center. I construct the zipcode urbanicity/rurality distinction based on population density (described in detail in the Appendix).

within the county instead of out of the county. Among active physicians in NC, 12 percent change zipcode of employment. Of physicians who moved, 60 percent moved within their counties, while 26 percent moved out of the county to an urban zipcode and 14 percent moved out of the county to a rural zipcode. In light of the computational and data constraints discussed above and in an effort to preserve the urban/rural distinction that characterizes zipcodes and counties, I differentiate location alternatives in the empirical model by moves within and across counties and by urbanicity/rurality of the destination zipcode as summarized in Table 2.3.

Table 2.3: Summary Statistics: Activity and Movement by Year

Activity and Movement				
Year	Remain in the Same Location in NC	Move within NC	Move out of NC	Become Inactive
2003	91.75	3.98	1.84	2.43
2004	76.41	17.96	4.26	1.37
2005	80.37	14.12	3.15	2.36
2006	86.92	9.17	2.22	1.7
2007	86.41	9.46	2.31	1.82
2008	83.14	12.07	2.76	2.02
2009	82.05	15.25	1.44	1.26
2010	82.92	13.44	2.4	1.24
2011	81.45	14.72	2.23	1.6
Total	83.42	12.36	2.48	1.73

Movement and Rurality Conditional on a Move within NC				
Year	Move within the County to an Urban Zipcode	Move within the County to a Rural Zipcode	Move out of the County to an Urban Zipcode	Move out of the County to a Rural Zipcode
2003	34.49	7.72	38.74	19.06
2004	49.32	8.38	27.03	15.27
2005	45.75	8.2	29.93	16.12
2006	47.62	7.88	27.66	16.85
2007	45.59	7.56	30.13	16.72
2008	47.33	6.17	29.6	16.9
2009	65.33	5.87	18.45	10.34
2010	61.15	5.59	23.82	9.44
2011	58.97	5.88	24.6	10.55
Total	53.14	6.87	26.29	13.71

Note: Statistics based on 165,668 person-year observations including a physician's first year in the survey.

Facility

The physician licensure database also provides current type of facility in the primary, secondary, and tertiary locations of employment. The twelve facility types are: locum tenes,[8] solo practitioner's office, free-standing clinic, group office, staff or group model HMO, hospital-outpatient department, hospital-emergency room, hospital-other, medical school or parent university, nursing home/extended care facility, telemedicine, and others. Missing values in facility type are replaced using a similar procedure as with primary location of

[8]The locum tenes facility type describes an employment situation similar to substitute teaching in the education profession. Locum tenes physicians generally work a lower number of hours than physician who are permanently placed.

practice. The previous or future facility type serves as the facility type in a year when it is not reported if zip-codes match across years of primary, secondary, or tertiary location of employment. To simplify the number of categories of facilities, I group the facilities into six categories: group practices, solo practices, hospital-ER related, hospital-Not ER related, Medical School/Parent University, and others. Table 2.4 displays the distribution of facility type among physicians in NC by year.

Table 2.4: Summary Statistics: Primary Facility Type

Year	Group	Solo	Hospital: ER	Hospital: Non ER	Medical School	Other
2004	51.45	14.53	5.74	17.62	8.69	1.98
2005	50.40	15.23	5.58	16.99	9.32	2.47
2006	49.13	14.63	5.49	16.99	10.51	3.25
2007	48.58	14.14	5.63	17.65	10.67	3.33
2008	47.67	13.58	5.76	18.56	10.93	3.50
2009	47.93	13.02	5.68	19.30	10.85	3.21
2010	47.25	12.38	5.74	20.11	11.31	3.21
2011	46.17	11.91	5.77	21.34	11.59	3.23
2012	45.49	11.58	5.89	22.13	11.67	3.25
Total	48.06	13.33	5.71	19.13	10.70	3.08

Note: Statistics based on 155,767 person-year observations among active physicians excluding their first year in the sample.

Table 2.5 depicts year-to-year probabilities of changing facility and changing county conditional on staying active in NC. A relatively larger proportion of physicians (20.38 percent) change facility when they change locations than physicians who change facility but not location (7.07 percent).

Table 2.5: Location and Facility Change Summary

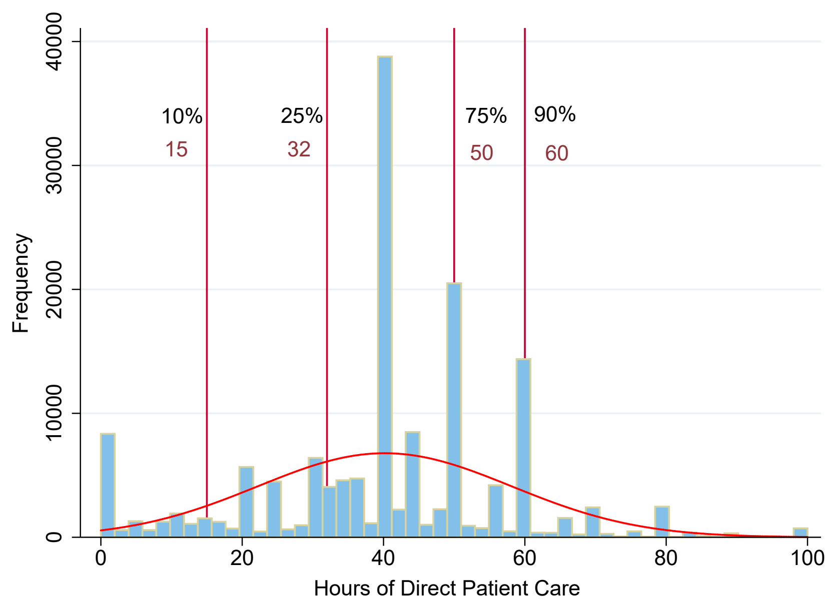
	Do Not Change Facility	Change Facility	Total
Remain in the Same Location in NC	92.93	7.07	100
Move within the County to an Urban Zipcode	84.03	15.97	100
Move within the County to a Rural Zipcode	83.36	16.64	100
Move out of the County to an Urban Zipcode	73.13	26.87	100
Move out of the County to a Rural Zipcode	73.07	26.93	100
Total	79.62	20.38	100

Note: Statistics based on 158,682 represents the person-year observations among active physicians excluding their first year in the sample.

Hours of Direct Patient Care

Each active physician provides average hours worked per week in the locations of practice. In estimation, I focus on the number of self-reported direct patient care hours (i.e., I do not model non-patient-related activities). I cap the number of patient care hours at 100 hours per week, which is over two standard deviations above the mean. In the research sample, there are only 914 person-year outliers who reported greater than 100 hours per week and 8,106 (5.2 percent) report zero hours of direct patient care. African Americans report a greater average number of hours of direct care than any other group while Caucasians report the lowest average number of hours. Female physicians report fewer patient care hours on average than their male counterparts across all races. Figure 2.3 depicts a histogram of hours of direct patient care using all person-year observations of active physicians (with specific percentiles in red).

Figure 2.3: Histogram of Hours of Direct Patient Care



2.3.2 Specialty, Experience, and Demographics

As described in Section 3.1, I observe the activity, location, facility, and hours of direct patient care behaviors of physicians annually. Important determinants of these annual behaviors are specialty and years of accumulated work experience, which are determined prior to entry into the dataset. In this section, I describe the available data on physician's specialty and discuss construction of experience when first observed since I do not observe all physicians upon graduation from medical school or after completion of residency or fellowship. I also detail the demographic characteristics available in the dataset.

Specialty

Although physicians are allowed to update their primary/secondary areas of practice specialty each year, less than 1 percent of physicians in the research sample change their primary area of practice. There are 166 specialties recorded in 2003 and 55 additional specialties appear in the ten subsequent years of observable data. In total, there are 221 different types of medical specialties listed in the database.

Rather than model selection among 221 alternatives, I collapse the large number of physician specialties into five categories that conform to the guidelines set forth by the AMA: (1) primary care physicians/generalists, (2) medical specialists, (3) surgical specialists, (4) hospital-based specialists, and (5) other specialists. Primary care physicians, or generalists, act as the first contact and principal care provider for patients. They also coordinate between patient and specialist if additional care is needed. Unlike specialists, generalists require minimal diagnostic and therapeutic technology. Unlike generalists, specialists are trained to handle illnesses that may not occur frequently and that are more serious in nature. They are also more dependent on capital, such as equipment, laboratories, and advanced diagnostic technologies. Therefore, specialists are more likely to be constrained by their surrounding resources than generalists and are more likely to be attracted to environments with higher concentrations of technological capital. Also, specialists are differentiated by the degree of interaction with patients.

Areas of expertise that fall under generalist include family medicine, general internal medicine, general pediatrics and general OB/GYN. Medical specialists include those in allergy and immunology, cardiovascular disease, dermatology, gastroenterology, internal medicine sub-specialties (such as diabetes, endocrinology, geriatrics, hematology, infectious disease, nephrology, nutrition, and medical oncology rheumatology), pediatric subspecialties, pediatric cardiology, and pulmonary disease. Surgical specialists are those in general surgery, colon/rectal surgery, neurological surgery, obstetrics and gynecology, ophthalmology, orthopedic surgery, plastic surgery, thoracic surgery, and urology. Hospital-based specialists in are anesthesiology, anatomic/clinical pathology, and radiology. Other specialists have expertise in occupational or preventative medicine, or in mental health fields, such as rehabilitation and psychiatry.

The distribution of physician specialty differs across gender and race (Table 2.6). A larger percentage of minorities are generalists, especially among African Americans; only 35 percent of Caucasian physicians are generalists. With the exception of Asian physicians, who have the highest percentage of medical specialist (16.73 percent), Caucasian physicians are more likely to specialize than other races. The same pattern is found among female physicians, where more than half of female physicians are generalists.

Table 2.6: Summary Statistics: Distribution of Specialty by Race and Gender

	Primary-Care /Generalist	Medical Specialist	Surgical Specialist	Hospital Specialist	Other Specialist
Race					
Caucasian	35.03	16.28	21.32	20.69	6.69
African American	51.48	10.54	17.83	13.79	6.37
Asian	45.22	16.73	13.58	17.06	7.41
Hispanic	44.43	10.73	17.12	19.02	8.70
Other	44.02	16.13	15.32	18.08	6.44
Total	38.13	15.72	19.79	19.58	6.77
Gender					
Male	32.78	17.15	22.58	21.00	6.20
Female	50.75	12.36	13.24	15.54	8.11
Total	38.13	15.72	19.79	19.58	6.77

Note: Statistics based on 29,908 uniquely-identified physicians in the research sample. The percentage reported is the row percentage by race and gender.

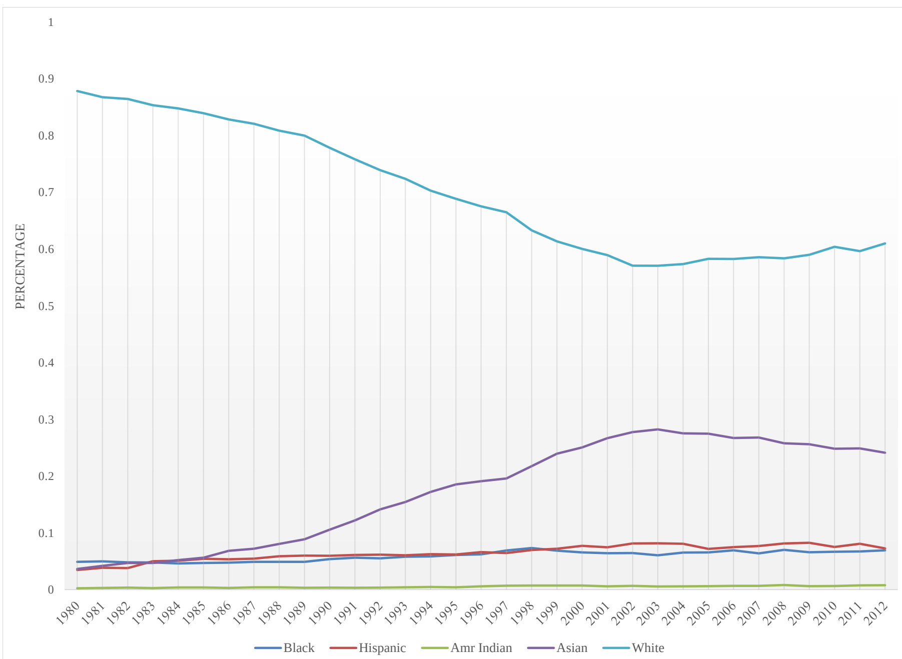
Experience

Each respondent must provide the year she first received her medical license, regardless of the state in which it was obtained. Thus, assuming continuous employment as a physician, the initial level of experience is recorded as the difference between the year of first observation in the research sample and the year of licensure. In the following years, if the respondent remains active, then an additional year of experience is gained. Table 2.7 reports the initial level of experience for physicians in the research sample by gender and race. Minority and female physicians have less experience than their counterparts, which reflects their more recent entry into the physician profession within NC due to policy changes that encouraged their entry in the late 1980s. On the national level, there is a similar influx of new minority physicians in the last decade. Figure 2.4 shows the race distribution of physicians by medical school graduation year between 1980 and 2012 and demonstrates a shift in the demographic composition of new physicians in the US. As the share of minority physicians increases overtime, a greater percentage of new physicians in NC (and, hence, in my research sample) are minorities. Thus, the average experience level of minority physicians tends to be lower than their counterparts. Among all physicians first observed in the research sample, 19.9 percent have zero years of experience (i.e., the year of entry in the sample is their first year of licensed practice).

Table 2.7: Summary Statistics: Experience by Race and Gender

	Median			Mean		
Race	All	Male	Female	All	Male	Female
Caucasian	7	9	3	10.73	12.38	6.18
African American	1	2	1	5.64	6.72	4.38
Asian	1	1	1	4.53	5.10	3.56
Hispanic	1	1	1	4.66	5.22	3.68
Other	1	1	1	4.19	4.78	3.02

Figure 2.4: Race Distribution of US Physicians by Graduation Year, 1980-2012



Demographics

Race, gender, and age are reported for all 29,908 physicians in the research sample. A self-reported race variable contains six mutually-exclusive options: Caucasian & Non-Hispanic, African American & Non-Hispanic, American Indian/Alaskan Native, Asian/Pacific Islander, Hispanic, Other (in estimation, American Indian/Alaskan Native are included in the group Other because it comprised less than 2 percent of the observations). Table 2.8 summarizes gender and race of physicians in the research sample. Overall, 70.2 percent of the uniquely-identified physicians are male and 29.8 percent are female, while 73.5 percent are Caucasian and

26.5 percent are minorities. Compared to the census data, there are larger proportions of Caucasian and Asian physicians than the populations of both races in NC. There are fewer African American and Hispanic physicians in NC relative to their population in NC. The gender and racial distributions of physicians change during the ten years of data as more minority and female physicians enter the labor force. Table 2.9 summarizes age of the research sample. On average, male Caucasian physicians in the sample are older with a median age around 50. Female and minority physicians are generally younger.

Table 2.8: Summary Statistics: Physician Gender and Race

Race	Male	Female	Total	Census Percent
Caucasian/Not Hispanic	76.85	65.47	73.46	64.40
African American/Not Hispanic	6.09	12.27	7.93	22.00
Asian	8.96	12.36	9.97	2.60
Hispanic	2.23	3.00	2.46	8.90
Other Race	5.87	6.90	6.18	2.10

Note: Statistics based on uniquely identified 29,908 physicians in the research sample. The last column contains the demographic information from the 2013 US Census 2013 in North Carolina.

Table 2.9: Summary Statistics: Physician Age By Race and Gender

	Median Age			Mean Age		
Race	All	Male	Female	All	Male	Female
Caucasian/Not Hispanic	43	45	38	44.60	46.46	39.47
African American/Not Hispanic	38	42	35	40.18	42.53	37.43
Asian	37	38	35	39.61	40.97	37.28
Hispanic	38	40	35	40.48	42.17	37.50
Other	37	38	35	39.56	40.67	37.33

2.3.3 Salary Data

Hourly wages reflect the price of an hour of work in a particular labor market. In a high skilled labor market, a worker's market value is his/her annual salary. In the partial equilibrium analysis of physician labor supply that I perform, I assume that market salary as well as the demand for labor are pre-determined and known to physicians. Unfortunately, the Physician Licensure Database does not contain salary information and, to my

[8] North Carolina Census Quick Facts: http://quickfacts.census.gov/qfd/states/37000.html

knowledge, there is no publicly- or privately-available salary database for NC physicians at the individual level. To capture variation in physician labor income, I use two datasets: the Physician Salary Survey Report from the Hospital and Healthcare Compensation Service (HHCS) and the NC Occupational Employment Statistics (OES) of Healthcare Practitioners. Salary data from 2003 to 2012 are reported in real dollars with 2003 as the base year.

The HHCS physician survey provides the average salary (S_{sft}) for physicians in 48 different specialties (s) and 6 different facilities (f) across 10 years (t). The survey also reports the 25 percentile (Q^1), median, and 75 percentile (Q^3) of salaries for each specialty/facility/year combination. The OES database records salaries of health care practitioners in each of the 100 counties in NC for each year. The OES data reflect averages over all health care practitioners, not exclusively physicians. I calculate for each county k a z-score, z_{kt}, to reflect the number of standard deviations from the average state salary. Using information from both datasets, I am able to construct a physician salary in each of the 100 NC counties for 48 specialties, 6 facilities, and 10 years. Using the interquantile range formula, I solve $IQR = Q^3_{sft} - Q^1_{sft} = 2\Phi^{-1}(0.75)\sigma_{sft} \approx \frac{27}{20}\sigma_{sft} \approx 1.349\sigma_{sft}$ where σ_{sft} represents the standard deviation of salaries in each specialty, facility, and year. Using the formula, average salary for a physician in county k with specialty s in facility f at time t is defined as $\overline{S_{ksft}} = \overline{S_{sft}} + [\sigma_{sft} \times z_{ksft}]$.[9]

When county salary data are missing from OES, I infer unknown values through extrapolation using data from the previous years and/or future years and the average wage inflation data collected by the St. Louis Federal Reserve. The wage inflator reflects seasonally-adjusted salaries of private employees, which includes physicians. If multiple years of the data are not known, I extrapolate information from the American Community Survey (ACS) which also reports full-time, year-round employment information for health care professionals in NC at the county level.

In addition to using this constructed average salary variable (which varies by county, year, specialty, and facility), I generate a salary rank variable by year. I arrange salaries of each county in ascending order such that the highest ranking represents the highest salary level in all counties in a particular year. I assign an average salary and the salary rank to each physician in each year based on her county, specialty and facility.

2.3.4 County-Level Data

I obtain county-level data from Log Into North Carolina (LINC), which combines census data from both state and federal agencies. The 100 counties of NC differ greatly in wealth, size, and the demographics of its

[9]For example, if the average salary of Alamance County physicians is two standard deviations below the mean wage in NC, then all physicians in Alamance county (regardless of facility and specialty) are assigned a salary two standard deviations below the mean salary.

residents. I link the county-level data with the location of the physician's primary practice. The county-level data include basic demographic variables that summarize the size, age, and race distributions of the population in each of the 100 counties in NC. Other variables capture characteristics of the county that might describe the local labor market and local amenities that influence movement into or out of a county. These variables include the number of unemployed, income per capita, total retail sales, number of industry establishments, and education-related variables (i.e., public school personnel, public school personnel with a masters level education, average SAT verbal score, average SAT math score, total public school expenditures, and total public school expenditure from the local government). Importantly, the county-level variables also include characteristics of the medical care market in the county. The variables chosen reflect the potential demand for medical care as well as medical care supply-related characteristics (i.e., total number of pregnancies, total number of births, number of hospital beds, number of long-term care beds, and total number of Medicaid eligible and Medicare enrollees). Summary statistics for available county-level data are provided in Table 2.10 and are averaged over the 100 counties by year. The county-level characteristics capture local amenities, the employment market (potentially relevant for both the physicians and spouse), local demand for medical care professionals, and medical care supply characteristics (i.e., complements and substitutes).[10]

To capture physician supply characteristics more accurately, different types of physicians are aggregated to the county level using the physician licensure database. Detailed physician supply in the county may capture the degree of complementarity or substitutability of different types of physicians. It may also proxy for the local physician network and reflect ease of referral or competition.

[10] All dollar-valued variables are adjusted to reflect real values in year 2003 dollars.

Table 2.10: Summary Statistics: County-Level Data of North Carolina

	Mean	Std. Dev.	Min	Max
Demographics				
Population (10,000s)	9.06	13.15	0.41	96.26
Older Population (65+) (1,000s)	11.11	12.10	0.64	86.11
Caucasian/Non-Hispanic (1000s)	60.82	79.51	2.26	586.20
African American/Non-Hispanic (1000s)	19.48	36.40	0.02	296.22
Asian (1000s)	1.06	4.97	0.01	51.10
Hispanic (1000s)	6.89	13.31	0.10	121.5
Other (1000s)	3.16	8.15	0.05	72.7
Medical Care Market				
Births (1000s)	1.24	2.06	0.04	14.90
Pregnancies (100s)	15.11	26.37	0.41	192.33
Hospital Discharges (1000s)	9.83	12.26	0.34	87.82
Acute Care/Hospital Beds (100s)	2.05	3.28	0.00	19.96
Long-term Care/Nursing Home Beds (100s)	4.42	4.99	0.00	31.00
Midlevel Practitioners	62.55	123.39	0.00	922.00
Registered Nurses (1000s)	0.83	1.57	0.01	10.69
Medicaid Eligibles (10,000s)	1.56	1.83	0.08	14.32
Medicare Insured (10,000s)	1.07	1.21	0.06	8.87
Primary Care Physicians	65.35	118.31	0.00	880
Medical Specialists	32.32	80.74	0.00	643
Surgical Specialists	36.35	75.96	0.00	538
Hospital Specialists	33.04	73.08	0.00	547
Other Specialists	12.64	30.94	0.00	228
Amenities				
Gross Retail Sales (Billion $)	0.98	2.05	0.01	18.88
Unemployed (100s)	33.45	51.83	1.12	515.15
Per-capita Income (10,000 $)	3.00	0.52	1.88	5.17
Industrial Establishments (100s)	21.81	39.25	0.66	285.18
Local Education Expenditures (10 Million $)	2.60	4.67	0.07	33.80
Total Education Expenditures (10 Million $)	10.91	15.78	0.72	114.99
Public School Personnel (100s)	10.10	14.46	0.00	102.40
Public School Personnel with MA (100s)	3.17	5.03	0.12	40.8
Average SAT Math (100s)	4.94	0.33	3.91	5.84
Average SAT Verbal (100s)	4.76	0.33	3.74	5.70

Note: Statistics based on 100 counties in NC averaged over all years (2003-2012).

2.4 Theoretical Motivation

This section presents a theoretical model of the professional and geographical decisions of NC physicians. The primary objective of the theory is to motivate the empirical specification in terms of the individual physician and county-level characteristics that affect physician's professional and geographical decisions. The community characteristics are of particular interest, and I use the theoretical framework to explain how local characteristics enter as both push factors (i.e., increase the probability of leaving an area) and pull factors (i.e., increase the probability of locating in a particular area). The theory also allows me to discuss the assumptions that must be made to reduce the set of location alternatives to a number feasible for estimation. Because the theoretical model is not parameterized, solved, and estimated, I ignore some issues that would complicate full solution of the physician's optimization problem. I address these concerns after providing the theoretical motivation.

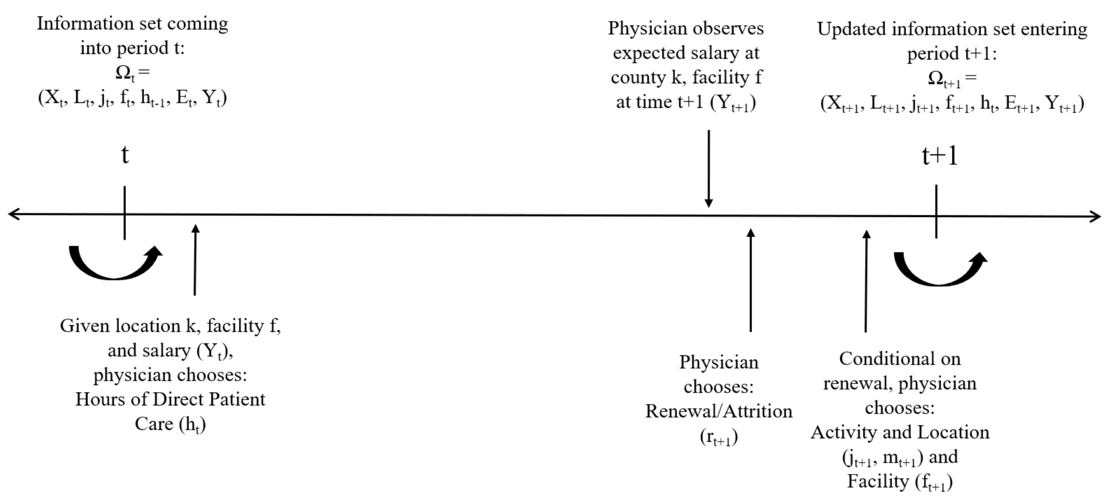
Physicians are forward-looking agents who make decisions based on current utility, budget and time constraints and discounted expected future utility. Since behavior today affects future utility, I use a dynamic framework in modeling physician's decisions. I assume that time is discrete with a period being a year. Figure 2.5 displays the timing of physician professional behaviors, where a period is defined as one year. At the beginning of period t, an active physician practicing in NC county or zipcode k_t and facility f_t selects how many hours (h_t) of direct patient care to engage in during this period. At the end of the period, active physicians have gained an additional year of experience and decide whether or not to renew their NC medical licenses for next period (r_{t+1}). If the physician decides not to renew her license, she attrits from the estimation sample. Conditional on renewing the license, a physician decides on activity and location (j_{t+1}) and facility (f_{t+1}) for the next period. Physicians who renew their licenses select whether or not to remain actively practicing medicine. If active, they select the geographical region in which to practice. The alternatives, j, for the activity location decision ($j_{t+1} = j$) are:

$$j = \begin{cases} 0 & \text{inactive} \\ k & \text{active in NC in zipcode or county } k \text{ where } k \in [1, \ldots, K] \\ K+1 & \text{active in NC but not practicing in NC} \end{cases}$$

Inactive physicians ($j_{t+1} = 0$) and physicians who choose to practice outside of NC ($j_{t+1} = K + 1$) are not followed in my data. As explained below, they receive a terminal value function, W^0_{t+1} and W^{K+1}_{t+1}, that depends on their specialty and experience through period t. In the empirical work, I focus on the location decisions of active physicians with NC licenses, and model attrition out of the active status among NC-practicing physicians.

The physician enters each period with an information set, or a vector of state variables Ω_t, composed of individual-specific exogenous characteristics (X_t) at time t;[11] a vector of location characteristics for all counties in NC ($L_t = [L_t^1, \dots, L_t^K]$, where $k \in [1, \dots, K]$ and $K = 850$ zipcodes or and $K = 100$ counties); and the history of her previous employment-related behaviors. The pre-determined state variables include specialty (S_1) upon completion of medial school and a residency program, current activity and location (j_t), current facility (f_t), hours of direct patient care in the previous period, (h_{t-1}), experience up to period t (E_t), and annual salary for the current period (Y_t).[12]

Figure 2.5: Timing



A physician derives current period utility from both pecuniary and non-pecuniary benefits of working in county k at facility f at time t. Specifically, the physician receives utility from consumption (C_t), leisure (l_t), location characteristics in county k (L_t^k), the type of facility ($f_t = f$), and an unobserved (by the researcher) component (ε_t^u). At the beginning of each period, the physician selects hours of direct patient care, $h_t = h$, conditional on the activity, location, and facility selected at the end of the last period. The value of alternative $h_t = h$ at the beginning of period t is:

$$\begin{aligned} V_h(\Omega_t, \varepsilon_t) = {} & U(C_t, l_t, f_t = f, L_t^k; X_t, E_t, h_{t-1}) + \varepsilon_{ht}^u \\ & + \beta\{\max\ [W^0(\Omega_{t+1}), W_{j'f'}(\Omega_{t+1})_{j'=\{1,\dots K\}, f'=\{1,\dots F\}}, W^{K+1}(\Omega_{t+1})]\} \\ & \forall t, \forall h = 0, \dots, \mathrm{H} \end{aligned} \tag{2.1}$$

Total consumption is constrained by the annual salary ($Y_t \mathbb{1}[h_t > 0]$) minus the cost of moving (M_t), where

[11] The vector X_t includes variables for age, gender, and birth country/state.

[12] In the theoretical model section, the subscript i on individually-varying variables is omitted for notational simplicity.

$C_t = Y_t \mathbb{1}[h_t > 0] - M_t \mathbb{1}[j_{t-1} \neq j_t]$. Leisure ($l_t$) in each period is constrained by total time (Υ) minus hours worked (h_t) and time required to move from one location to another (N), where $l_t = \Upsilon - h_t - N\mathbb{1}[j_{t-1} \neq j_t]$. The salary received at time t depends on physician specialty (S_t), facility ($f_t = f$), and county ($j_t = k$), where $Y_t = Y(S_t, f_t, j_t)$. The terminal value of inactive status is denoted by $W^0(\Omega_{t+1})$ and the terminal value of activity outside of NC is $W^{K+1}(\Omega_{t+1})$. The value of selecting activity and location (j') and facility (f') at the end of the period is:

$$W_{j'f'}(\Omega_{t+1}) = \mathbb{E}_t[\phi_{j'f'}(L_t^{j'}, S_t, f_t) \times \max_{h'} \; V_{h'}^{k'f'}(\Omega_{t+1}, \varepsilon_{t+1})] \tag{2.2}$$

where ϕ_{jf} reflects the probability of receiving a job offer from facility f' in location $j' = k'$ and depends on physician specialty and the contemporaneous location characteristics for each county and facility type.[13] The utility a physician receives in the current period depends on the amenities and medical care market characteristics in the previously determined location ($j_t = k$) and facility (f_t). To capture effects of habit or a change in routine, I allow current utility to depend on previous hours of direct patient care (h_{t-1}).

At the end of the period, the values of the location and facility for the next period alternatives depend on the current location characteristics (or push factors) as well as the location characteristics of alternative locations (or pull factors). The push factors may influence the location decision directly by lowering the value of staying in the current location via expectation of future levels of those location characteristics. The push factors could also influence the location decision indirectly through hours worked (e.g., high medical demand in a county that leads to long hours in period t may raise the value of a new location with lower demand for medical services). The location characteristics may serve as pull factors if they raise the utility of an alternative location. Additionally, characteristics in other locations affect the probability of a job offer.[14]

2.5 Empirical Framework

Solution to the physician's optimization problem would yield probabilities of the behaviors (activity, location, facility, and hours worked) observed in the data. However, the large set of alternatives (among 100 counties or 850 zipcodes and 12 facilities) renders solution and estimation difficult. Although it is possible to

[13] The model defined in the theoretical section is a partial equilibrium model, where the market demand for physicians is exogenous to the individual physician and is impacted by exogenous demand-side variables such as county-level demographic, insurance coverage, and other medical care demand characteristics.

[14] If we wanted to solve the optimization problem, we must make an assumption regarding a physician's beliefs about future location characteristics. I could assume perfect foresight or assume that physicians use their current knowledge of all location characteristics (L_t) to forecast the characteristics of each location next period (i.e., Markov beliefs, adaptive expectations). Alternatively, I could assume a physician expects the characteristics to remain the same next year, and is surprised by new values of these characteristics. I do not take a stance here because I do not solve this model explicitly due to computational demands. The empirical model, described in Section 5, requires that I limit the choice set and, hence, the use of location characteristics.

conceptualize the decision problem of physicians as one over all county and facility alternatives within NC, estimation of the probability of moving from a specific county-facility combination to another county-facility is computationally costly if one tries to include observed variables to explain that movement.

To simplify the problem while also retaining as much information about locations as possible, I first collapse location alternatives of active physicians to three: remain in the same zipcode of employment in NC, move to another zipcode of employment in NC, and move outside NC. Conditional on moving to another zipcode of employment in NC, I then expand the location alternatives among those who moved within NC in order to consider four additional categories: move within the county to an urban zipcode, move within the county to a rural zipcode, move out of the county to an urban zipcode, and move out of the county to a rural zipcode. For facility alternatives, I simplify the twelve alternatives to six alternatives. The facility categorization comes from the HHCS physician survey, which was introduced in the data section and is used in my average salary construction. Thus, conditional on remaining active, a physician chooses among six facility types and seven location types. Because it is also important to examine physician labor supply in areas of need, I allow location alternatives to reflect rural and metropolitan counties as defined by the Sheps Center and rurality of zipcode using another method as described further in the Appendix for Chapter 2.

2.5.1 Per-Period Employment Behaviors

Conditional on being active in NC at time t, the redefined activity and location alternatives ($j_{t+1} = j$) in the empirical model are:

$$j = \begin{cases} 0 & \text{inactive in t+1} \\ 1 & \text{active in NC and do not change zipcode of employment in t+1} \\ 2 & \text{active in NC and change zipcode of employment in t+1} \\ 3 & \text{active and move out of NC in t+1} \end{cases}$$

Conditional on changing zipcode of employment within NC in $t+1$, the movement alternatives $m_{t+1} = m$, are:

$$m = \begin{cases} 1 & \text{move within the county to an urban zipcode in t+1} \\ 2 & \text{move within the county to a rural zipcode in t+1} \\ 3 & \text{move out of the county to an urban zipcode in t+1} \\ 4 & \text{move out of the county to a rural zipcode in t+1} \end{cases}$$

The reduced set of the facility alternatives, $f_{t+1} = f$, are:

$$f = \begin{cases} 1 & \text{Group Practice} \\ 2 & \text{Solo Practice} \\ 3 & \text{Hospital: ER Related} \\ 4 & \text{Hospital: Non ER related} \\ 5 & \text{Medical School/Parent University} \\ 6 & \text{All other types} \end{cases}$$

I use the theoretical framework to derive demand behaviors as functions of the physician's information entering period t, Ω_t, and the primitive parameters of the optimization problem (if the utility function parametrization was specified). A first-order Taylor series expansion of the resulting demand functions yields reduced form equations that I specify below. While physicians choose some behaviors (location and facility) jointly, I specify the demand for each behavior but allow for correlation across periods through observed determinants over time (i.e., physician characteristics such as work experience and lagged employment behaviors) and unobserved individual characteristics (such as permanent preferences for living in large cities). The correlation structure also allows for correlation across the many physician behaviors within a time period using observed characteristics as well as time-varying unobserved physician characteristics (such as the birth of a child or an unobserved shock that permeates all employment behaviors within the period). This joint correlation through unobservables is modeled using random effects and requires that I integrate the (conditional) likelihood of the observed outcomes over the distribution of these unobservables, which by definition is unknown. Rather than impose a distributional assumption that might be incorrect, I approximate the distribution of these unobserved components by estimating the support of the unobserved heterogeneity distribution (using discrete mass points) and their associated weights jointly with the parameters capturing the effects of the observed characteristics (Mroz and Guilkey, 1992; Mroz 1999).[15] This flexible method allows me to incorporate important omitted (in the literature) aspects of physician employment behaviors such as dependence on past behaviors and simultaneity of many jointly-chosen behaviors.

To make explicit the correlation in the resulting probabilities or densities of observed behaviors that form

[15] Mroz (1999) found that when the unobserved heterogeneity is not (jointly) normally distributed, the discrete factor approximations perform better than maximum likelihood estimation that assumes normality. The Monte-Carlo study also found that when the distribution of the unobserved component is normally distributed, there is little bias or efficiency loss using the discrete factor random effect method.

the estimated likelihood function, I decompose the unobserved heterogeneity in each equation into three components, $\varepsilon_t^e = \mu^e + \nu_t^e + \epsilon_t^e$, where μ represents permanent individual unobserved heterogeneity, ν_t is serially-uncorrelated time-varying individual unobserved heterogeneity, and ε_t is idiosyncratic unobserved heterogeneity.[16]

At beginning of each period, the continuously-valued hours of direct patient care in period t is a function of the following determinants:[17]

$$h_t = f^H(X_t, E_t, Y_t, L_t^k, \mathbb{1}[j_t = 2], \mathbb{1}[m_t = 2,4], f_t, h_{t-1}, Z_t^D) + \mu^H + \nu_t^H + \epsilon_t^H \tag{2.3}$$

where ϵ_t^H is the serially-uncorrelated error explaining variation in hours worked and follows a normal distribution and Z^D are exclusion restrictions that identify (beginning of period) outcomes.[18] In addition to its dependence on demographic variables, work experience, and salary, the hours outcome depends on current county characteristics, indicators of a recent move and a move to a rural area, current facility type, and lagged hours worked. Empirically, the hours outcome is observed only for those physicians who remain active in NC from the period to the next. This selection is modeled by the following license renewal, activity and location, and facility probabilities.

Conditional on working in county k and facility f in period t, I observe the activity, location, and facility outcomes for the next period. However, these outcomes are observed only if a physician is licensed in NC. The probability of not renewing a medical license or attriting from the estimation sample ($r_{t+1} = 0$) relative to renewing ($r_{t+1} = 1$) in period $t + 1$ is:

$$ln(\frac{p(r_{t+1} = 0)}{p(r_{t+1} = 1)}) = f^R(X_t, E_{t+1}, Y_t, L_t^k, f_t, h_t) + \mu^R + \nu_t^R \tag{2.4}$$

Conditional on not attriting from the sample, the probabilities of being inactive ($j_{t+1} = 0$), being active and changing zipcode of employment ($j_{t+1} = 2$), or being active and changing employment to outside NC ($j_{t+1} = 3$) relative to being active and not changing county of employment ($j_{t+1} = 1$) in period t+1, are:

[16]The subscript e denotes the relevant behavior: hours (H), activity and location (J, M), and facility (F). Because the unobserved error in each equation is individual specific, the error decomposition, with the individual subscripts i, is: $\varepsilon_{it}^e = \mu_i^e + \nu_{it}^e + \epsilon_{it}^e$. Theoretically, the permanent component of this specification, μ, is individual specific. Empirically, I estimate this unobserved heterogeneity as a random effect, not as a fixed effect as the notation may suggest. That is, an individuals contribution to the likelihood of her observed behaviors is the product of the probabilities of each behavior, e, conditional on observed explanatory variables and the value of the permanent unobserved heterogeneity, where I integrate the conditional likelihood contribution over the estimated distribution of the unobserved heterogeneity. Similarly, ν_{it} is individual specific, and I model it as a random effect. The likelihood function is provided in section 2.5.3.

[17]The functions represented in the below section $f(\cdot)$ are linear functions with higher order and interaction terms.

[18]Discussion of these exclusion restrictions is provided in the Identification Section 5.4.

$$ln(\frac{p(j_{t+1}=j|r_{t+1}=1)}{p(j_{t+1}=1|r_{t+1}=1)}) = f^J(X_t, E_{t+1}, Y_t, L_t^k, \mathbb{1}[j_t=2], \mathbb{1}[m_t=2,4], f_t, h_t) + \mu^J + \nu_t^J$$
$$\text{for } j = 0,2,3, \tag{2.5}$$

Conditional on being active and changing zipcode of employment ($j_{t+1} = 2$), the probabilities of moving within the county to a rural zipcode ($m_{t+1} = 2$), or moving out of the county to an urban zipcode ($m_{t+1} = 3$), or moving out of the county to a rural zipcode ($m_{t+1} = 4$) relative to moving within the county to an urban zipcode ($m_{t+1} = 1$) in period t+1, are:

$$ln(\frac{p(m_{t+1}=m|j_{t+1}=2)}{p(m_{t+1}=1|j_{t+1}=2)}) = f^M(X_t, E_{t+1}, Y_t, L_t^k, \mathbb{1}[j_t=2], \mathbb{1}[m_t=2,4], f_t, h_t) + \mu^M + \nu_t^M$$
$$\text{for } m = 2,3,4 \tag{2.6}$$

The probabilities of each facility type ($f_t \in [2,6]$), relative to group practice ($f_{t+1} = 1$) in period $t+1$, are:

$$ln(\frac{p(f_{t+1}=f|r_{t+1}=1)}{p(f_{t+1}=1|r_{t+1}=1)}) = f^F(X_t, E_{t+1}, Y_t, L_t^k, \mathbb{1}[j_t=2], \mathbb{1}[m_t=2,4], f_t, h_t) + \mu^F + \nu_t^F \tag{2.7}$$

The empirical framework includes the characteristics of the county in which the physician is currently employed, $L_t^k, j_t = k$, instead of the characteristics of each county (L_t). As stated in the beginning of Section 5, the set of activity and location outcomes are reduced from 852 or 102 alternatives (i.e., 850 zipcodes or 100 NC counties, 1 option for outside of NC, and 1 option for inactivity) to a set of seven alternatives for simplicity. This simplification restricts my ability to include county characteristics from other counties, L_t^{-k}, where $-k$ denotes counties that are not chosen. However, if does allow for movement to locations characterized as rural or urban. Thus, the empirical model includes the relevant theoretical push factors on physician professional and geographical outcomes and restricts the pull factors to rural and urban characterizations.

2.5.2 Initial Conditions

Because I first observe (in the data) physicians in the middle of their career, some endogenous state variables are non-zero and present an initial conditions problem in estimation. Rather than treating these variables as exogenous, I model them using reduced form, static equations. All of the initial condition equations are jointly-estimated with the employment behavior equations and are modeled as functions of exogenous individual characteristics X_t and appropriate exclusion restrictions, Z_t^I.

The endogenous, initially-observed variables include specialty, experience up to period $t = 1$, facility, hours worked, and metropolitan or rural county location. Variables used to identify the initial conditions are based on the self-reported birth country if the physician is foreign-born and birth state if the physician is born in the

US. Additionally, corresponding market characteristics of these locations at year one affect the probability of (1) specialty S, (2) experience E_1, (3) facility f_1, (4) rural or metropolitan location $\mathbb{1}[j_1 = 2, 3]$, and (5) hours of direct patient care h_0^I, but should not affect the subsequent per-period physician behaviors conditional on these observed initial conditions.

The probabilities of each specialty type ($S_t \in [2, \ldots, 5]$), relative to primary-care/generalist in the first period, are:

$$ln\left(\frac{p(S_t = s)}{p(S_t = 1)}\right) = f^S(X_t, Z_t^I) + \mu^S + \epsilon_t^S \quad \text{for } s = 2, 3, 4, 5; \;\; t = 1 \tag{2.8}$$

The continuously-valued level of experience in the first observable period (E_t) is specified as:

$$E_t = f^E(X_t, S_t, Z_t^I) + \mu^E + \epsilon_t^E \quad \text{for } e = 0, \ldots, 69; \;\; t = 1 \tag{2.9}$$

The probabilities of initially-observed facility type relative to group practice ($f_t = 1$) are:

$$ln\left(\frac{p(f_t = f)}{p(f_t = 1)}\right) = f^{F^I}(X_t, S_t, E_t, Z_t^I) + \mu^{F^I} + \epsilon_t^{F^I} \quad \text{for } f = 2, 3, 4, 5, 6; \;\; t = 1 \tag{2.10}$$

The probability of working in a rural county ($j_t = 2$) relative to working in a metro county in the first period ($j_t = 1$) is:

$$ln\left(\frac{p(j_t = 2)}{p(j_t = 1)}\right) = f^{J^I}(X_t, S_t, E_t, Z_t^I) + \mu^{J^I} + \epsilon_t^{J^I} \quad \text{for } t = 1 \tag{2.11}$$

The hours of direct patient care in the first period is specified as:

$$h_t = f^{H^I}(X, S_t, E_t, f_t, Z_t^I) + \mu^{H^I} + \epsilon_t^{H^I} \quad \text{for } h = 0, \ldots, 100; \;\; t = 1 \tag{2.12}$$

2.5.3 Likelihood Function

The unconditional likelihood function for N physicians observed for T periods is:

$$\begin{aligned}
\mathcal{L}(\Theta) = \prod_{i=1}^{N} \Bigg\{ \sum_{m=1}^{M} \theta_m \prod_{s=1}^{5} \mathbb{P}(S_1 = s|\mu_m)^{\mathbb{1}[S_{i1}=s]} \cdot \prod_{f=1}^{6} \mathbb{P}(f_1 = f|\mu_m)^{\mathbb{1}[f_{i1}=f]} \cdot \prod_{j=1}^{2} \mathbb{P}(j_1 = j|\mu_m)^{\mathbb{1}[j_{i1}=j]} \\
\cdot \Phi^E(\cdot|\mu_m) \cdot \Phi^{H^I}(\cdot|\mu_m) \\
\cdot \prod_{t=2}^{T_i} \Bigg[\sum_{l=1}^{L} \psi_l \Phi^H(\cdot|\mu_m, \nu_{lt}) \cdot \Pr(r_{t+1} = 0|\mu_m, \nu_{lt})^{\mathbb{1}[r_{it+1}=0]} \\
\cdot \Big[\Pr(r_{t+1} = 1|\mu_m, \nu_{lt}) \cdot \prod_{j=0}^{3} \big[\Pr(j_{t+1} = j|\mu_m, \nu_{lt}) \cdot \prod_{m=1}^{4} \big[\Pr(m_{t+1} = m|\mu_m, \nu_{lt}) \\
\cdot \prod_{f=1}^{6} [\Pr(f_{t+1} = f|\mu_m, \nu_{lt})]^{\mathbb{1}[f_{it+1}=f]\cdot\mathbb{1}[j_{it+1}=2]} \big]^{\mathbb{1}[m_{it+1}=m]\cdot\mathbb{1}[j_{it+1}=2]} \big]^{\mathbb{1}[j_{it+1}=j]} \Big]^{\mathbb{1}[r_{it+1}=1]} \Bigg] \Bigg\}
\end{aligned} \tag{2.13}$$

where Θ represents the vector of estimated parameters on implicitly-included regressors as well as the parameters of the correlated unobserved components. I estimate the permanent and time-varying distributions of unobserved heterogeneity using a discrete approximation of their distributions, where θ_m is the probability of observing the m^{th} mass point of the permanent heterogeneity distribution and ψ_l is the probability of observing the l^{th} mass point of the time-varying heterogeneity distribution. These weights and the associated vectors of mass points (μ and ν_t) are jointly estimated via full information maximum likelihood along with the other parameters of the model.

2.5.4 Identification

Time-varying exogenous individual and location-specific characteristics identify the dynamic, multiple-equation system. For physicians who moved between adjacent periods, the difference in these county characteristics, Z_t^D, affects hours of direct patient care conditional on hours of care in the previous location. These aforementioned variables affect number of hours of patient care, but they do not affect end of period outcomes conditional on hours worked. For example, the direction and size of the *change in* demand for physician services may affect current patient care hours but the *level of* demand in the current location affects end of period movement. Additionally, the lagged hours of direct patient care (h_{t-1}) is included in the current hours equation to capture habit or break in routine, but should not affect activity, location, and facility decisions at the end-of-the period (for the current period) conditional on current hours. The dynamic equation system is also identified by the histories of exogenous time-varying determinants across individuals over time. The non-linear functional forms of the likelihood contributions provide additional identification. Finally, a few covariance restrictions on the unobserved heterogeneity is necessary for identification as well. Table 2.11 summarizes the jointly-estimated set of equations and their determinants.

Table 2.11: Specification Summary for Jointly Estimated Behaviors and Outcomes via FIML

	Explanatory Variables			
	Pre-Determined Endogenous	Exogenous	Unobserved Heterogeneity	Likelihood Contribution
Behaviors				
Hours of direct patient care (h_t)	$j_t, f_t, h_{t-1}, E_t, Y_t, S_t$	X_t, L_t, Z_t^D	$\mu^H, \nu_t^H, \epsilon_t^H$	Φ^H
Attrition/Renewal (r_{t+1})	$j_t, f_t, h_t, E_{t+1}, Y_t, S_t$	X_t, L_t	$\mu^R, \nu_t^R, \epsilon_t^R$	$P(r_{t+1} = r), r = 0, 1$
Active and Movement (j_{t+1})	$j_t, f_t, h_t, E_{t+1}, Y_t, S_t$	X_t, L_t	$\mu^J, \nu_t^J, \epsilon_t^J$	$P(j_{t+1} = j)$, $j = 0, 1, 2, 3$
Movement and Rurality (m_{t+1})	$j_t, f_t, h_t, E_{t+1}, Y_t, S_t$	X_t, L_t	$\mu^M, \nu_t^M, \epsilon_t^M$	$P(m_{t+1} = m)$, $j = 1, 2, 3, 4$
Facility (f_{t+1})	$j_t, f_t, h_t, E_{t+1}, Y_t, S_t$	X_t, L_t	$\mu^F, \nu_t^F, \epsilon_t^F$	$P(f_{t+1} = f)$, $f = 1, \ldots, 6$
Initial Conditions				
Specialty (S_1)		X_t, Z_t^I	μ^S, ϵ_t^S	$P(S_1 = s)$, $s = 1, 2, 3, 4, 5$
Experience (E_1)	S_t	X_t, Z_t^I	μ^E, ϵ_t^E	Φ^E
Facility (f_1)	S_t, E_t	X_t, Z_t^I	$\mu^F, \epsilon_t^{F^I}$	$P(f_1 = f)$, $f = 1, \ldots, 6$
Rural or Metro County (j_1)	S_t, E_t	X_t, Z_t^I	$\mu^J, \epsilon_t^{J^I}$	$P(j_1 = r)$, $j = 2, 3$
Hours of Direct Patient Care (h_1)	S_t, E_t, f_t	X_t, Z_t^I	$\mu^{H^I}, \epsilon_t^{H^I}$	Φ^{H^I}

2.6 Estimation Results

In this section, I begin by demonstrating how well the estimated model of physician professional behaviors fits the observed data. Then, I present and discuss briefly the significant and marginal effects of variables of interest. Lastly, I use the estimated data-generating process to simulate the short- and long-term impacts of alternative policy scenarios.

2.6.1 Model Fit

After estimating the coefficients from the dynamic multiple equation model using FIML and DFRE, it is essential to check whether the model captures the patterns displayed in the observed data. I use the estimated parameters to simulate physician professional and geographical behavior from the initial period forward, and use the simulated values of the endogenous variables to update behavior and outcomes in the following periods. The model that performed the best in terms of statistical fit has four mass points for the permanent unobserved heterogeneity and two mass points for the time-varying unobserved heterogeneity. For each of the N replications of the sample in simulation, I draw a permanent type once and draw a time-varying type each period using the estimated distributions. A draw from the appropriate i.i.d. error distribution completes simulation of behaviors. The comparison between simulated outcomes and the observed data is shown in Table 2.12 and suggests that the estimated model fits the data well.[19]

Table 2.12: Per Period Summary Statistics for Model Fit

Outcome	Observed	Simulated
Activity and Movement	Mean	Mean
Do Not Move	83.42	84.29
Move within NC	12.36	12.21
Move out of NC	2.48	2.26
Inactive	1.73	1.23
Movement and Rurality (conditional on moving within NC)		
Move within the County to Urban Zipcode	53.14	52.47
Move within the County to Rural Zipcode	6.87	8.96
Move out of the County to Urban Zipcode	26.29	25.57
Move out of the County to Rural Zipcode	13.71	13.99
Facility		
Group Practice	47.82	47.10
Solo Practice	13.36	13.19
Hospital: ER Related	5.70	5.78
Hospital: Non ER related	19.19	19.42
Medical School/Parent University	10.79	11.02
Other	3.14	3.49
Hours worked	40.29	40.17

[19]Graphical comparisons by age or experience of the physician are available from the author.

2.6.2 Results from the Dynamic Multiple-equation Model

The estimated coefficients and their standard errors of variables that affect physician movement and activity, while allowing for correlation across equations and over time through modeling permanent and time-variant unobserved heterogeneity, are displayed in Table 2.13. Additional results regarding rurality, facility and hours worked are detailed in Appendix Tables A.8, A.9 and A.11. Here, I focus the discussion on the key variables of interest in this chapter including average hours and salary, individual characteristics and county-level market characteristics and amenities.[20]

An increase in current hours of direct patient care significantly decreases the likelihood of moving within NC relative to not moving. Theory suggests that more hours of direct patient care may be habit forming and induce the physician to stay in their current location rather than face uncertainty about future hours worked in another location.[21] I also find that an increase in the average salary reduces the likelihood of changing location of employment in NC relative to not moving. Importantly, the interaction term of rurality and average salary is negative and is greater in magnitude than the coefficient for average wage, which indicates that a higher average salary in rural areas decreases the likelihood of moving within NC. Conditional on a current rural zipcode and moving within NC, Table A.8 shows that physicians are 1.3 times more likely to move within county to another rural zipcode, relative to moving to an urban zipcode within county. Conditional on moving out of a county in NC with a current rural zipcode, physicians are 42 times more likely to move to a rural zipcode, relative to moving within county to an urban zipcode. Conditional on a current rural zipcode and moving within NC, physicians are 0.15 times as likely to move out of the county to an urban zipcode relative to moving within county to an urban zipcode. This finding echoes the persistence mechanism in physician migration where selection into rural or urban area reveals the type of location physician would most likely to move to conditional on moving.

Further, there are several findings regarding movement that are consistent with existing literature. An increased level of experience is associated with a decreased likelihood of movement. However, as age increases, the odds of moving increase. Controlling for age, more experience suggests a lower likelihood of being inactive, or increase in experience increases the odds of changing location and facility early in one's career, with evidence that movement is less likely later in ones's career. Although the coefficient for experience squared is positive and significant, the magnitude is small. Consistent with the literature, I find that a female physician is more

[20]The UH coefficients, standard errors, and estimated probability weights are listed in Appendix Table A.12.

[21] A physician with a greater number of hours of direct patient care in the current period is likely to work a larger number of hours in the next period, which supports the habit story in the theoretical model. A physician in a rural zipcode is also more likely to work more hours than their urban counterparts. African American and Hispanic physicians work 1.78 hours and 1.11 hours more than their Caucasian counterparts in a workweek, respectively. This finding is true for foreign born doctors as well, who work 1.63 more hours than native born physicians.

likely to switch her location and facility than a male physician. Because the data do not contain information in family structure, I cannot attribute this difference in behavior by gender to martial status or family size.

Several location characteristics significantly impact physician activity and movement. An increase in the numbers of public school personnel and of more educated public school personnel (those with Master degrees and above) deceases the likelihood of moving. On average, physicians in a county with a greater public school staff presence are 0.9 times as likely to move than their counterparts.[22] This finding is consistent with the hypothesis that physicians remain in locations with higher quality school systems.

Medical care market characteristics also impact movement. On the supply side, the number of mid-level practitioners, including ANPs and PAs, appears positively correlated with retention of physicians relative to not moving. Stange (2013) finds there is a complementary relationship between physicians and mid-level practitioners, while the Sheps Center model treats mid-level practitioners as substitutes for generalists. Consistent with Stange, I find that an increased number of mid-level practitioners decreases the likelihood of movement, conditional on remaining active. That is, physicians and mid-level practitioners are complementary. Indeed, mid-level practitioners must be overseen by a physician. Thus, an increased number of mid-level practitioners may require a greater number of physicians for supervision, explaining the reduced likelihood of physician movement. Interestingly, I also find that an increased number of mid-level practitioners increases the likelihood of becoming inactive. The larger number of midlevel practitioners may drive out physicians.

On the other hand, the number of RNs significantly increases physician movement. However, the effect of nurses differs among rural and urban areas, where an increase in RNs in a rural (urban) area decreases (increases) the likelihood of moving relative to not moving. In rural areas, the initial level of healthcare provision by all types of healthcare professionals is low relative to demand. A greater numbers of RNs in rural areas may decrease the likelihood of physician burnout through task allocation and thereby facilitate physician retention in those areas. On the other hand, RNs may serve as substitutes for physicians since multiple RNs can be overseen by a single physician, especially in areas where all types of healthcare professionals is high relative to demand. Therefore, the substitutability of RNs dominates in urban areas, while their ability to relieve burnout helps to retain physicians in rural areas.

[22] The county characteristics in the current model are in levels (and not normalized by population) while controlling for county-specific population. I have estimated the model with per-capita county characteristics as well. The odds ratio associated with public school staff per capita and educated public school staff per capita is 0.94 and 0.95, respectively.

Table 2.13: Estimation Results: Activity and Location Outcome at End of the Period

	Move within NC				Move out of NC				Inactive			
	Coeff	Signif.	SD	Odds	Coeff	Signif.	SD	Odds	Coeff	Signif.	SD	Odds
Current Average Salary (10,000 $)	-0.002	*	0.000	0.998	-0.012	***	0.003	0.988	-0.034	***	0.004	0.966
Average Salary × Rural	-0.011	***	0.003	0.989	0.012	***	0.004	1.012	0.009		0.006	1.009
Current Salary Rank	-0.001		0.001	0.999	-0.001		0.001	0.999	0.004	**	0.002	1.004
Current Hours of Direct Patient Care	-0.002	***	0.001	0.998	-0.001		0.001	0.999	-0.021	***	0.002	0.979
Experience	-0.043	***	0.007	0.958	-0.115	***	0.014	0.892	-0.147	***	0.016	0.863
Experience Squared (divided by 100)	0.085	**	0.036	1.089	0.054		0.091	1.055	0.513	***	0.077	1.670
Experience Cubed (divided by 10,000)	-0.023		0.052	0.977	0.131		0.149	1.14	-0.574	***	0.099	0.563
Current Rural Location	-0.018		0.031	0.982	0.238	***	0.061	1.269	-0.172	**	0.080	0.842
Moved in Previous Period	0.758	***	0.033	2.134	0.274	***	0.075	1.315	0.079		0.112	1.082
Facility (relative to Group Practice)												
Solo Practice	-0.075	**	0.033	0.927	0.383	***	0.064	1.466	-0.215	***	0.075	0.806
Hospital: ER Related	0.575	***	0.044	1.778	0.591	***	0.083	1.806	-0.048		0.126	0.953
Hospital: Non ER related	0.438	***	0.028	1.549	0.177	***	0.059	1.194	-0.058		0.082	0.943
Medical School/Parent University	-0.047		0.044	0.954	0.283	***	0.077	1.327	-0.442	***	0.097	0.643
Other Facility	0.492	***	0.049	1.635	0.643	***	0.101	1.901	1.260	***	0.087	3.524
Specialty (relative to Generalist)												
Medical Specialist	-0.119	***	0.031	0.887	0.193	***	0.060	1.213	0.099		0.072	1.104
Surgical specialist	-0.195	***	0.033	0.823	0.376	***	0.061	1.457	0.455	***	0.074	1.576
Hospital specialist	0.084	**	0.033	1.087	0.558	***	0.063	1.748	0.417	***	0.078	1.517
Other specialist	0.255	***	0.037	1.291	0.475	***	0.081	1.609	-0.268	***	0.09	0.765
Female	0.079	***	0.022	1.083	-0.212	***	0.041	0.809	0.659	***	0.054	1.933
Race (relative to Caucasian)												
African American	0.189	***	0.034	1.208	0.098		0.064	1.103	-0.255	**	0.103	0.775
Asian	-0.046		0.035	0.955	-0.072		0.058	0.931	-0.284	***	0.098	0.753
Hispanic	0.135	**	0.065	1.145	0.159		0.100	1.172	-0.257		0.179	0.773
Other Race	0.070	*	0.039	1.072	-0.042		0.071	0.958	-0.160		0.119	0.852
Foreign Born	0.028		0.031	1.028	0.136	**	0.054	1.146	-0.075		0.086	0.928
Age	-0.318	***	0.042	0.728	-0.608	***	0.076	0.544	-0.505	***	0.079	0.603
Age Squared (divided by 100)	0.600	***	0.085	1.822	1.121	***	0.159	3.067	1.058	***	0.148	2.880
Age Cubed (divided by 10,000)	-0.362	***	0.056	0.696	-0.653	***	0.107	0.521	-0.607	***	0.089	0.545
County Characteristics												
Population (10,000s)	0.051	***	0.007	1.053	0.040	**	0.016	1.041	0.000		0.019	1.000
Population × Rural	0.130	***	0.021	1.139	-0.002		0.040	0.998	0.054		0.063	1.056
Older Population (65+) (1,000s)	0.080	***	0.008	1.084	0.043	***	0.015	1.044	-0.037	**	0.018	0.964
Births (1000s)	-0.673	***	0.091	0.51	-0.027		0.175	0.974	0.438	**	0.214	1.550
Pregnancies (100s)	0.058	***	0.008	1.06	0.017		0.015	1.018	-0.046	**	0.018	0.956
Hospital Discharges (1000s)	-0.023	***	0.005	0.978	-0.006		0.01	0.994	-0.016		0.013	0.984
Acute Care/Hospital Beds (100s)	-0.179	***	0.016	0.836	-0.025		0.031	0.975	0.06		0.039	1.062
Long-term Care/Nursing Home Beds (100s)	-0.069	***	0.011	0.933	-0.086	***	0.022	0.918	-0.002		0.029	0.998
Midlevel Practitioners	-0.004	***	0.000	0.996	-0.005	***	0.001	0.995	0.001		0.001	1.001
Midlevel Practitioner × Rural	-0.001		0.002	0.999	0.005		0.004	1.005	-0.004		0.006	0.996
Registered Nurses (1000s)	0.320	***	0.058	1.377	0.242	**	0.111	1.273	-0.070		0.142	0.933
Registered Nurses × Rural	-0.367	**	0.169	0.693	-1.438	***	0.327	0.237	-0.286		0.449	0.751
Medicaid Eligibles (10,000s)	-0.241	***	0.029	0.786	0.022		0.057	1.022	0.167	**	0.077	1.182
Medicaid Eligibles × Rural	0.208	***	0.056	1.232	0.156		0.107	1.169	-0.079		0.150	0.924
Medicare Insured (10,000s)	-0.014		0.053	0.986	0.098		0.099	1.103	0.161	**	0.067	1.174
Medicare Eligibles × Rural	-0.532	***	0.099	0.588	0.122		0.198	1.130	-0.034		0.261	0.967
Primary Care Physicians	0.002	***	0.000	1.002	0.001	*	0.001	1.001	-0.002	**	0.001	0.998
Medical Specialists	0.001	***	0.001	1.001	-0.003	***	0.001	0.997	-0.002	*	0.001	0.998
Surgical Specialists	0.006	***	0.001	1.006	0.008	***	0.002	1.008	0.003		0.002	1.003
Hospital Specialists	0.002	***	0.001	1.002	0.001		0.001	1.001	-0.002		0.002	0.998
Other Specialists	-0.010	***	0.001	0.99	-0.001		0.002	0.999	0.006	**	0.003	1.006
Gross Retail Sales (Billion $)	0.261	***	0.018	1.299	0.106	***	0.037	1.112	0.056		0.047	1.058
Retail Sale × Rural	-0.103		0.089	0.903	0.327	*	0.170	1.387	0.057		0.226	1.059
Unemployed (100s)	-0.002	***	0.000	0.998	-0.002	**	0.001	0.998	-0.001		0.001	0.999
Per-capita Income (10,000 $)	0.018		0.041	1.018	0.02		0.079	1.021	-0.044		0.108	0.957
Industrial Establishments (100s)	-0.032	***	0.002	0.969	-0.027	***	0.005	0.974	-0.001		0.006	0.999
Local Education Expenditures (10 Million $)	0.045	**	0.018	1.047	0.04		0.037	1.041	0.027		0.050	1.028
Total Education Expenditures (10 Million $)	0.026	***	0.010	1.026	-0.004		0.020	0.996	0.035		0.025	1.036
Public School Personnel (100s)	-0.036	***	0.007	0.964	-0.027		0.017	0.973	-0.025		0.020	0.975
Public School Personnel with MA (100s)	-0.016	*	0.009	0.984	-0.055	***	0.02	0.946	0.000		0.022	1.000
Average SAT Math (100s)	-0.271	*	0.158	0.763	-1.705	***	0.302	0.182	-0.041		0.390	0.959
Average SAT Verbal (100s)	0.302	*	0.163	1.352	1.505	***	0.31	4.504	0.145		0.400	1.157
Year	1.015	***	0.057	2.76	1.079	***	0.11	2.943	-0.373	***	0.140	0.689
Year Squared	-2.218	***	0.127	0.109	-2.489	***	0.252	0.083	0.301		0.319	1.351
Year Cubed	1.402	***	0.084	4.064	1.607	***	0.168	4.989	-0.002		0.214	0.998
Constant	3.404	***	0.749	30.098	-14.338	***	0.677	0	6.610	***	1.700	742.483

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. The coefficients for the permanent unobserved heterogeneity and time-varying unobserved heterogeneity are listed in Table A.12.

2.6.3 Policy Experiments

Experiment A: Loan-Forgiveness Programs

In the past few decades, policymakers in the US have created multiple types of student loan forgiveness programs in order to attract physicians to rural and underserved areas. The most notable program is the National Health Service Corps (NHSC) loan repayment programs, which offers tax-free loan repayment assistance to support qualified physicians in rural or underserved areas. The qualified area of practice is generally specified by the area's Health Professional Shortage Area (HPSA) scores.[23] These programs offer up to $200,000 at the end of the physician's tenure in approved rural areas (normally for a two-year contract).[24] In addition to federal programs, individual states can offer additional payment to physicians in underserved areas. NC offers additional grants totaling up to $70,000 (capped at half of the total student loan amount) to physicians willing to commit five years serving in an HPSA through the Community Practitioner Program (CPP).[25] However, the effectiveness of these policies is debated as recent reports continue to show a significant shortage of physicians in underserved and rural areas. As noted by the AMA and American Academy of Family Physicians (AAFP), retention of physicians in rural and underserved areas remains a problem as physician demographics change in the US.[26] [27] Although the NHSC and many state programs use loan-repayment programs to draw new physicians to serve in areas of need, the majority of enrollees leave these areas after completion of the program (ASPE 2015).

To simulate these types of loan forgiveness programs, I consider three different ways of implementing a lump sum increase in non-labor income. The first simulation allows an increase in average salary for all rural areas of $200,000 or $100,000 in the first year (i.e., year 2003 at the time of the study). The second simulation allows a $200,000 increase in the average salary in all rural areas in the first year of practice for all physicians. The last

[23]Congress created the Health Professional Shortage Area (HPSA) indication and the National Health Service Corps (NHSC) in the 1970s to easily and clearly identify and assist areas in need of physicians and other health professionals. There are three types of HPSA designations: primary medical care, dental, and mental health. HPSAs can be geographic areas, population groups, or facilities. The most commonly used HPSA is a geographic area HPSA, which is based on the physician-to-population ratio in a defined area.

[24]Because loan forgiveness programs differ across states, I simulate two levels of loan forgiveness, $100,000 and $200,000. The loan forgiveness of $200,000 is used to simulate the most generous version of the loan forgiveness program in the US, while the $100,000 captures the average amount of loan forgiveness. In NC, eligible physicians receive funding from both Federal and State agencies. According to the NC Office of Rural Health from NCDHHS, physicians who are willing commit to the state's underserved rural communities are eligible for federal funding up to $50,000 and state loan repayment up to $100,000 (NCDHHS 2016). The second simulation with an average loan forgiveness amount of $100,000 is also comparable in cost to the reimbursement rate simulation in the next section.

[25]The CPP program is offered by the NC Medical Society and targeted toward practitioners who have a willingness to live and work in an underserved, often rural, part of the state.

[26]http://www.aafp.org/about/policies/all/rural-practice-paper.html

[27]http://journalofethics.ama-assn.org/2009/05/pfor1-0905.html

simulation targets only young physicians with under 10 years of experience and allows a $200,000 increase in average salary in all rural areas. Since the majority of the programs and grants are tax-free loan payments on both loan principal and interest, the simulation is similar to an increase in disposable income for physicians. An increase in average salary by $200,000 for one year for all rural areas is a generous version of the policy. Given that the average rural annual salary is around $220,000 dollars in the time period of the study, the simulation allows for almost a doubling of income for rural physicians. However, the generous version of the policy allows us to observe whether an increase in lump sum salary affects physician location behavior and retention in the best case scenario. Table 2.14 shows the difference between the likelihood of movement averaged over all years between the baseline simulation without the policy and the respective policy simulations. As shown in the table, a lump-sum increase in salary decreases the likelihood of moving within NC but by a small amount.

However, retention of physicians in rural areas is another important aim of the policy. To evaluate the retention of physicians in the same rural area, I calculate the probability of moving away after one year or after two years of service in a rural area conditional on observing a move during the simulated time periods.[28] An increase in retention is captured by a significant decrease in the probability of moving away from the same area. Table 2.15 shows that a lump-sum increase in non-labor salary slightly decreases the probability of moving away after one or two years of service for both male and female physicians. This finding supports the literature that physicians tend to move to rural areas with loan forgiveness programs, but they only stay until the expiration of their contract and retention of physicians after program expiration is low.[29]

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[28] I have generated other indicators to capture retention, but this is the most narrow definition of retention which would allow us to accurately capture whether or not the policy has an effect on physician retention in the same location of employment.

[29] In addition to assessing physician retention rates associated with policy intervention, I examine whether the physicians who remain in a county are similar to those who leave. Importantly, we may care about the quality of physicians who remain in the rural areas. Since there are no quality measures in the physician licensure database, I rely on observable physician characteristics to proxy for physician quality. Table A.16 and A.17 exhibit physician demographics in all counties and in only rural counties for each policy simulation compared with the benchmark simulation. Across gender, race, nationality, age, experience, and specialty types, physicians are not significantly different between the benchmark model and different types of policy simulations. These results suggest that heterogenous responses to policy changes, conditional on unobserved heterogeneity, will not generate differences in quality in different areas.

Table 2.14: One-Time Lump-Sum Increase in Non-Labor Income Simulation

	Activity and Movement				Movement and Rurality Conditional upon Moving			
Percentage Change in Probability by Scenario	Do Not Move	Move within NC	Move out of NC	Become Inactive	Move within County to Urban Zipcode	Move within County to Rural Zipcode	Move out of County to Urban Zipcode	Move out of County to Rural Zipcode
Increase salary of all rural counties by $200,000 in year 2003	1.07	-1.40	-8.53	-29.43	-6.72	36.57	2.09	3.72
Increase salary of all rural counties by $200,000 in all years	1.56	-3.79	-9.54	-34.33	-5.06	37.89	5.41	-9.75
Increase salary of all rural counties by $200,000 in all years for young doctors	1.35	-3.68	-6.16	-29.83	-8.58	33.22	5.46	6.16

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table 2.15: Lump Sum Non-Labor Income-Retention

	All		Male		Female	
Percentage Change in Probability by Scenario	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years
Increase salary of all rural counties by $200,000 in 2003	-0.24	-0.96	-0.14	-0.44	-0.83	0.58
Increase salary of all rural counties by $200,000 in all years	-3.17	-2.57	-4.68	-4.24	-0.92	0.14
Increase salary of all rural counties by $200,000 in all years for young doctors	-0.37	-0.13	-1.38	-0.15	0.92	-0.68

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Experiment B: Proportional Increase in Salary

Another policy that has been used by some countries to draw physicians to rural areas and retain them is an increase in reimbursement rates for physicians. The rationale behind this targeted incentive is the belief that physicians are rational economic agents. If some form of economic inducement enhances the reimbursement for rural services, then physicians are more likely to locate in these areas and remain there. This approach has been met with some success in Britain, Canada, and Australia, using a variety of bonuses to increase reimbursement for selected rural practitioners (Rosenblatt 2006). One of the reimbursement strategies in the US has targeted care provided for Medicaid and Medicare recipients. For example, the Omnibus Budget Reconciliation Act (OBRA) of 1987 provided a bonus payment of 5-percent of the amount paid by Medicare for physicians providing care in rural primary care Health Professional Shortage Areas (HPSAs). In 1991 the bonus payment was increased to

10 percent, and eligibility was expanded to include reimbursement for services provided by physicians of certain specialties in urban HPSAs.

To simulate this type of change and to differentiate between an expansion in Medicare and Medicaid coverage, I allow a percentage increase in salary of 5, 10, and 20 percent in rural areas. Tables 2.16 and 2.17 show the simulated probabilities of movement and retention in the same county of employment. A 5-percent increase in average salary in all rural counties increases the likelihood of a physician staying in the same zipcode by 3.96 percent and decreases the probability of movement by 13.03 percent. Conditional on moving, a proportional increase in salary does not increase the probability of moving to rural areas, within the county and out of the county. However, the retention of physicians in the same county increases with an increase in reimbursement rate and there is a decreasing marginal return to larger increases in salary (10 or 20 percent). Table 2.17 shows that a 5-percent increase in average salary decreases the probability of moving after one year by 11.7 percent and of moving after two years by 6.7 percent. The effect is larger among male physicians (12.2 percent) than female physicians (4.3 percent). Although a percentage increase in salary in rural areas is not effective in inducing physician movement, the reimbursement policy is effective at increasing physician retention in rural areas. The behavior difference between men and women is consistent with the literature, where female physicians are more likely to move for non-pecuniary reasons such as moving for a spouse's job opportunities.

Table 2.16: Proportional Income Increase Simulation

	Activity and Movement				Movement and Rurality			
Percentage Change in Probability by Scenario	Do Not Move	Move within NC	Move out of NC	Become Inactive	Move within County to Urban Zipcode	Move within County to Rural Zipcode	Move out of County to Urban Zipcode	Move out of County to Rural Zipcode
Increase salary of all rural counties by 5% in all years	3.96	-13.03	-35.71	-46.74	13.05	10.95	-6.06	-44.47
Increase salary of all rural counties by 10% in all years	3.98	-13.20	-35.59	-46.57	12.81	9.86	-5.27	-44.49
Increase salary of all rural counties by 20% in all years	4.06	-13.71	-35.55	-46.74	12.31	11.77	-5.17	-43.69

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table 2.17: Proportional Salary Increase-Retention

	All		Male		Female	
Percentage Change in Probability by Scenario	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years
Increase salary of all rural counties by 5% in all years	-11.69	-6.69	-12.24	-8.04	-4.33	-3.71
Increase salary of all rural counties by 10% in all years	-14.21	-7.05	-14.69	-8.59	-4.43	-4.22
Increase salary of all rural counties by 20% in all years	-15.41	-6.98	-15.27	-8.33	-8.11	-4.74

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Experiment C: Change in the Composition of Medical Professionals

Policy makers have also attempted to influence physician behavior by changing the composition of their substitutes and complements. A recent MGMA publication shows a positive effect of mid-level practitioners (i.e., APNs and PAs) in areas with a physician shortage. To simulate an increase in mid-level practitioners, I allow a 5-percent increase in all rural areas. To simulate a shock to physician complements in rural areas, I allow a 5-percent increase in RNs for all rural areas. Although there are no policies enacted that target RNs specifically, an increase in rural physician resources or funding can be translated to an increased ability to hire more nurses.

Table 2.18 shows the effect of these two simulations. An increase in mid-level practitioners decreases the likelihood of remaining in the same area and moving. However, the likelihood of being inactive increases 2.8 percentage points (i.e., physicians are 1.6 times more likely to become inactive compare to the physicians who did not receive the policy), which supports the theory that an increase in physician substitutes could induce physicians to exit the labor force. Conditional on moving, physicians are 5.17 percent less likely to move within the county to an urban area and 31.29 percent more likely to move within the county to a rural zipcode and 18.05 percent more likely to move out of the county to an urban zipcode and 30.24 percent less likely to move out of the county to a rural zipcode. On the other hand, a 5-percent increase in RNs increases the probability of moving by 15 percentage point (121 percentage increase or 1.2 times more likely) and decreases the probability of staying in the same area of employment by 13.8 percentage point (16.56 percentage decrease). Conditional on moving, the policy also has a sizable effect on physician relocation behavior by increasing the likelihood of moving within the same county to a rural zipcode by 25.8 percentage point (3.75 times more likely).

In terms of retention, Table 2.19 shows that an increase in midlevel practitioners significantly increases the probability of moving after one or two years of service by 15.7 percent and 8.3 percent respectively for all physicians. Combined with the increase in inactivity, an increase in midlevel practitioners in rural areas allows physicians to exit the labor force earlier and decrease their stay in rural areas. On the other hand, an increase in RNs decreases the probability of leaving after one or two years of service by 13.8 percent and 2.7 percent. This finding could mean that an increase in RNs, a complement to physicians in areas with an existing shortage, may decrease the likelihood of burn out in those areas and decrease movement away from rural counties. Similar to the previous reimbursement rate experiment, males are more receptive to the policy change than their female counterparts.

Table 2.18: Increase in Midlevel Practitioners or RN Simulation

	Activity and Movement				Movement and Rurality			
Percentage Change in Probability by Scenario	Do Not Move	Move within NC	Move out of NC	Become Inactive	Move within County to Urban Zipcode	Move within County to Rural Zipcode	Move out of County to Urban Zipcode	Move out of County to Rural Zipcode
Increase midlevel practitioners in rural counties by 5% in all years	-1.71	-9.37	-10.14	163.59	-5.17	31.29	18.05	-30.24
Increase RN in rural counties by 5% in all years	-16.56	121.43	-20.21	-39.70	-0.19	375.72	-58.23	-75.81

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table 2.19: Increase in Midlevel Practitioners or RN Simulation-Retention

	All		Male		Female	
Percentage Change in Probability by Scenario	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years
Increase midlevel practitioner in rural counties by 5% in all years	15.71	8.30	15.27	7.24	15.30	8.97
Increase RN in rural counties by 5% in all years	-13.76	-2.70	-15.27	-3.80	-3.32	-1.93

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Experiment D: Increase in Medicaid and Medicare Eligibles

The recent changes in Medicare and Medicaid have altered the programs' eligibility requirements, which could potentially affect physician behavior. Under the Patient Protection and Affordable Care Act ("Obamacare"), Medicaid eligibility for U.S. citizens and legal residents increased significantly. The law allows adults without dependent children to qualify for coverage with income up to 133 percent of the poverty line.

To see the change in physician professional and geographical outcomes, I first allow a simple 10-percent increase in the number of Medicaid and Medicare eligibles in rural counties. This type of simulation is different from the second set of policy experiments that capture an increase in reimbursement rates for Medicare and Medicare eligibles. Tables 2.20 and 2.21 report the changes in the probabilities of moving and retention. An increase in Medicare and Medicaid eligibles slightly decreases the likelihood of moving. Conditional on moving, an increase in Medicaid eligibles increases the probability of movement within the county to a rural area by 29.74 percent and out of the county to an urban area by 18.29 percent. Similar to an increase of midlevel practitioners, an increase in Medicaid eligibles increases physician inactivity by almost 1.39 percentage points (180 percentage increase or 1.8 times more likely). The finding is similar to an increase in Medicare eligibles. In both simulations, the probability of moving away after one or two years of service increases across genders. An increase in Medicaid or Medicare eligibles increases the likelihood of moving away after one (two) year of service by 22.2 (10) percent or 21.6 (10.9) percent, respectively. The finding is consistent with physicians moving away from rural areas because Medicaid and Medicare patients have a lower reimbursement rate, higher reimbursement wait time, and more complex paperwork than private insurance. The effect is similar in magnitude for both male and female physicians.

Table 2.20: Increase Medicare or Medicaid Eligibles Simulation

	Activity and Movement				Movement and Rurality			
Percentage Change in Probability by Scenario	Do Not Move	Move within NC	Move out of NC	Become Inactive	Move within County to Urban Zipcode	Move within County to Rural Zipcode	Move out of County to Urban Zipcode	Move out of County to Rural Zipcode
Increase Medicaid in rural counties by 10% in all years	-2.32	-8.12	-7.45	180.32	-5.12	29.74	18.29	-30.13
Increase Medicare in rural counties by 10% in all years	-2.35	-7.99	-2.58	173.92	-5.32	29.90	18.39	-29.62

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table 2.21: Increase Medicare or Medicaid Eligibles Simulation-Retention

	All		Male		Female	
Percentage Change in Probability by Scenario	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years
Increase Medicaid in rural counties by 10% in all years	22.17	9.97	21.32	9.36	22.58	10.03
Increase Medicare in rural counties by 10% in all years	21.56	10.87	20.77	10.16	20.65	10.08

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

The aforementioned simulations consider an increase in Medicare and Medicaid coverage, while holding the population of other insurance recipients constant or assuming that the increase in public insurance only affected the uninsured population. This assumption could be unrealistic because, theoretically, an increase in public insurance would affect the privately-insured and uninsured population due to a crowding-out effect.

Dubay (1999) defines the potential crowd-out effect and outlines a topography of transitions from private to public insurance. He categories the new public enrollees into four groups: (1) transitions from uninsured to publicly insured; (2) involuntary transitions from Employer Sponsored Insurance to public insurance (e.g. job loss); (3) voluntary transitions from Employer Sponsored Insurance to public insurance; and (4) publicly insured who gain eligibility for Employer Sponsored Insurance, but remain on public insurance.

Crowd-out effects are commonly defined as the latter two categories of new enrollees and can occur when an individual drops private insurance due to a public coverage expansion or retains subsidized coverage when an employer sponsored offer becomes available. Early work by Cutler and Guber (1996) find that 50 percent of the increase in Medicaid was associated with a decrease in private insurance after Medicaid coverage was expanded to pregnant women and children between 1987-1992. Recent studies found a much lower crowd-out estimates for the same Medicaid expansions and the later Childrens Health Insurance Program/CHIP (Gruber & Simon, 2008; Thorpe & Florence, 1998; LoSasso & Buchmueller, 2004; Shore-Sheppard 2008; Ham & Shore-Sheppard, 2005). In an aggregating study by Sommers et al. (2007), the authors find private to public substitution for children covered by CHIP ranging from a low of 7.4 percent to a high of 19.1 percent using ten case studies in different states. For the adult population, several studies have found that there is minimal substitution of private insurance by public insurance in low income parents and/or adult in poverty (Aizer & Grogger, 2003; Dubay & Kenney, 1997; Kronick and Gilmer, 2002), but a significant reduction in private coverage for the near-poor and overall population (Kronick and Gilmer, 2002; Busch and Duchovny, 2005). However, many of the studies did not consider the potential decrease in private insurance from job loss or minimal availability of employer-sponsored coverage among low income workers. To focus on the new Medicaid enrollees from the ACA using survey data from Ohio, Seiber and Sahr (2011) found that substitution effect, or crowding out effect, remain low because it affects low-income adults (up to 133 percent FPL). More specifically, they found only 2.9 percent to 4.6 percent of new Medicaid adults substituted public for private coverage in the data after controlling for involuntary substitution. Of the voluntary substitution, two-thirds report that they could not afford the insurance offered by their employer. They also found the voluntary substitution remained low for families earning above 100 percent to 150 percent of poverty level because all transitions from private coverage to Medicaid (both voluntary and involuntary) are only 10 percent higher than the previously studied group. The same result is confirmed by a more recent article in the New England Journal of Medicine by Frean, Gruber, and

Sommers (2016). Since the passage of ACA, the insured rate has dropped from 16 percent to 9 percent and 44 percent of coverage gains is due to enrollment of previously eligible adults and children, 19 percent of coverage is gained due to enrollment of adults who became newly eligible in 2014, and 37 percent of the gains are due to premium subsidies, but there was no significant reduction in private coverage as a result of the Medicaid expansion. Therefore, my previous simulations under the assumption that public insurance expansion affects only the uninsured population could be applied to the ACA Medicaid expansion because it did not crowd out private insurance.

Since most expansion of public insurance is coupled with an increase in physician salary to compensate for the increase in workload (e.g., US states that expanded Medicaid under ACA also increased reimbursement rate for physicians), a more realistic simulation for an area with an increase in public insurance would includes a simultaneous increase in salary for physicians. Table 2.22 shows that by including an increase in salary for physicians in conjunction with Medicaid expansion, majority of the decrease in retention from the previous simulation is negated, which could explain the physicians supply remaining relatively stable geographically after ACA is implemented in the after 2012.

Table 2.22: Increase Medicaid Enrollees and Salary Simulation (ACA) -Retention

	All		Male		Female	
Percentage Change in Probability by Scenario	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years	Prob of Moving after One Year	Prob of Moving after Two Years
Increase Medicaid in rural counties by 10% and increase salary by 5% in all years	4.25	1.68	6.61	2.63	3.16	-2.88

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

2.7 Conclusion

This research uses a dynamic multiple-equation approach to examine physician professional and geographic outcomes in North Carolina. In particular, the results provide insights into the underlying mechanisms behind physician intra-state migration and the effectiveness of policy interventions. Using data on the population of physicians in NC from 2003 to 2012, I jointly model physicians' dynamic behavior relating to activity, location, facility, and hours of direct patient care. In this model, I allow physicians' behavior histories, individual characteristics, and time-varying county-level characteristics that capture amenities, number of physician substitutes or complements, and demand for healthcare professionals to affect physicians' current behaviors.

Simulations based on the estimated model demonstrate several major findings. Firstly, simulated loan forgiveness programs that aim to attract and retain physicians in rural areas are not as effective as a simulated increase in physician reimbursement rates. Although the simulated loan forgiveness policy is the most generous version of the loan forgiveness program, I find that the policy does not significantly decrease the likelihood of movement nor does it decrease the probability of moving away from rural areas after one or two years of service (i.e., retention). This finding is congruent with previous findings where a majority of the enrollees in loan forgiveness programs leave underserved areas after completion of the program. However, a 5-percent increase in rural county physician salary, simulated as an increase in reimbursement rate, decreases the probability of moving away from the same rural area significantly, and male physicians are more receptive to policy changes than their female counterparts.

Secondly, a change in the composition of healthcare providers in a rural area significantly affects physician movement and retention in the same area of employment. A 5-percent increase in midlevel practitioners in rural counties not only increases the probability of physicians moving away from the area after one or two years of service but also increases the likelihood of a physician becoming inactive. However, a 5-percent increase in RNs in rural counties significantly decreases the likelihood of physician leaving rural areas.

Lastly, considering the simulated effects of Medicaid and Medicare expansion on physicians, I find that both policy experiments increase physician movement away from their county of service and increase the likelihood of inactivity. The findings could be explained by physicians moving away from rural areas or transitioning into inactivity because Medicaid and Medicare are more complicated and time-costly than private insurance.

There are several important extensions that can be explored in future research. First, the current model is a partial equilibrium model and takes the demand for medical professionals as given. Hence, the simulation captures the behaviors of physicians in light of the assumption that labor demand is fixed. A two-sided model that includes the demand for healthcare professionals, as well as physician labor supply, would be more accurate in capturing the general equilibrium effects that occur when health care policy changes. Policies such as building a new hospital in a rural area or restructuring rural healthcare clinics could be tested under the general equilibrium model. Secondly, the research sample only includes active licensed physicians after completion of medical school and residency. Although initial selection into rural areas is considered in the current model, a more in-depth analysis of professional behaviors could be performed with data that include medical school selection and residency training, as well as initial employment, location, and facility type.

CHAPTER 3

O PHYSICIAN, WHERE ART THOU? IDENTIFYING THE EFFECT OF PHYSICIAN SUPPLY ON AMBULATORY CARE SENSITIVE CONDITION ADMISSIONS

3.1 Introduction

Ambulatory Care Sensitive Conditions (ACSC) are preventable or manageable with access to a primary care physician and medication, and may lead to hospitalization when not treated. Hospitalization rates related to these conditions is a manifestation of an unnecessarily ailing population and can be an expensive problem for the individual patients as well as the society. Research has shown that hospitalization for ACSC is eight times more expensive than a visit to a primary care physician (PCP) for ACSC (outpatient care) (Galarraga et al. 2015) and that ACSC constitute as many as half of all hospitalizations (depending on the classification used) in the US. For these reasons, improved access to preventative care for ACSC is one of the most important goals in healthcare today. Because many costly federal and state programs are implemented with this goal, researchers have studied the relationship between the supply of PCPs (the source of preventative care for ACSC) and hospitalization for ACSC. However, the results in both the health policy and health management literatures are mixed.

The findings of the extant literature range from the presence of more PCPs in an area decreases hospitalization for ACSC, has no effect, or even increases hospitalizations for ACSC. The current research suffers from two statistical problems that could, theoretically, produce each of these outcomes and, empirically, lead to incorrect inference about the effect of PCPs on hospitalizations for ACSC. The first and most critical issue is the problem of reverse causality or simultaneity bias. That is, although the number of PCPs may affect hospitalization for ACSC, physicians tend to locate in areas where there is a high incidence of these or any other illness (i.e., ACSC admissions also affect the number of PCPs or an increase in ACSC would attract more physician due to the increase in demand for physician services). Ignoring this feedback effect would result in an underestimation of the effect of PCPs i.e., make PCPs appear less effective in preventing hospitalizations for ACSC, having no effect on ACSC or even make them appear to increase hospitalizations for ACSC.[1] The second problem, omitted variable bias, results when a variable that affects both the number of occurrences of ACSC in a county and the decision of a physician to locate in a county is not controlled for in the analysis. The omitted variable could make the

[1]That is, if we assume the simultaneity bias is positive.

effect of PCPs on hospitalizations for ACSC appear spuriously larger or smaller.[2] The problem of simultaneity bias is not addressed in any of the existing literature while omitted variable bias is a problem in most existing studies.

Due to these issues, the Ordinary Least Squares (OLS) method commonly used in the literature is not capable of delivering unbiased and consistent parameter estimates. This chapter addresses this particular endogeneity issue by exploring an exogenous change in the physician labor force stemming from the federal and state-level policy called Health Professional Shortage Area (HPSA) designation. The chapter also addresses the issue of omitted variable bias by including a set of county-level characteristics. I use the Regression Discontinuity (RD) design to correctly identify the causal relationship between PCP supply and ACSC admissions. RD is a type of quasi-experimental design that evaluates the causal effects of interventions (e.g., a policy change on the physician supply) by assigning a cutoff or threshold above or below which an intervention is assigned. By comparing observations lying closely on either side of the threshold, RD is able to estimate the average treatment effect of the intervention on the dependent variable of interest.

For my analyses, I use the North Carolina physician licensure database, hospital discharge data, and aggregate county-level variables from 2003-2007. Individual physician and patient information are aggregated to the county-level through zipcodes and matched to county characteristics. A broad selection of ACSC ailments appropriate for diverse inpatient data across different patient demographics are used, as well as subcategories of ACSC, such as chronic, acute, and preventable ailments. I also include a rich set of county characteristics that address the potential for omitted variable bias.

Using the constructed database, the OLS method, which fails to address simultaneity or omitted variable bias, produces a positive relationship between PCPs and ACSC using my data, where an increase in PCP supply increases ACSC admissions. However, after accounting for both reverse causality and omitted variable using RD and a set of county-level characteristics, I find a significant negative relationship between PCP supply and ACSC admissions. This analysis provides strong evidence that an increased supply of PCPs decreases admissions for ACSC, which has large ramifications for health care costs. The results support calls for programs aimed at redistribution of PCPs by population. I use two separate model specifications to study the effect of PCPs on hospitalization for ACSC; one in levels while controlling for population and another that normalizes all variables by population. Both models reveal a similar negative relationship. After controlling for aggregate county-level

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[2] For example, consider the amount of air pollution in a county: Increased air pollution would be associated with a higher incidence of ACSC, but it would also tend to dissuade physicians from living in that county. This unobserved variable would make the coefficient more negative than it would be if this omitted variable is controlled for. Such an effect would make PCPs seem better than they are in preventing hospitalization from ACSC.

variables such as income, the number of Medicare eligible persons, and hospital resources, I find that whether the county is urban or rural has no significant impact on hospitalizations for ACSC. This finding dispels the notion that living in a rural area alone has a negative impact on hospitalization for chronic conditions. On the subcategories of ACSC, I find physician supply has the strongest effect on chronic ACSC while the effect is the lowest and insignificant with preventable ACSC.

Additional analyses are performed by age group, gender, and race to evaluate whether there are heterogeneous effects by patient demographics. Access to physicians has a slightly higher effect on female patients than their male counterparts, while patients in age group (40-64) and (65-85) benefit most from access to primary care doctors. I did not find significant differences across races, which means that access to physicians has a similar effect on all races after controlling for economic variables.

The next section breaks the existing literature into two groups and briefly describes some of the findings. Section 3 gives a brief history of the past and present policies enacted by the government to deal with the uneven distribution of physicians in the United States, which are used as policy instruments in our analysis. Data constructed for this chapter and their respective summary statistics are presented in Section 4. Section 5 describes the empirical model using RD and Section 6 shows the results. Section 7 concludes the analyses with directions for future research.

3.2 Literature Review

Although numerous studies in public health and health policy examine ACSC admissions, the relationship between ACSC conditions and access to physicians is often overlooked or not sufficiently addressed. Among studies that measure the effect of the availability of PCPs on ACSC, the results are mixed. In this section, I review the literature on the definition of ACSC and the relationship between ACSC and PCP access.

Literature concerning ACSC is divided into two strands. One strand of research evaluates the selection of ailments that have been classified as ACSC over time. Because ACSC designation was developed initially as a measure of access to care for the non-elderly population, a critical examination of the selection of ailments across time and population-at-risk is required to construct the ailment database used in this chapter. The other strand of research studies the effect of access to PCPs on hospitalization for ACSC.

Rutstein (1976) first measured the quality of medical care using counts of unnecessary or preventable ailments. In the paper, he provided a list of hundreds of ailments separated into groups, such as “unnecessary disease”, “unnecessary disability”, “unnecessary untimely death”, and “others ailments”. Due to advances in the medical technology and quality of care overtime, the last 40 years has seen an almost complete eradication of several of the diseases on the list such as smallpox, polio, plague, and yellow fever. The set of preventable ailments has been updated while keeping true to the general qualifications over time. Existing papers (Billings et al., 1993; Institute of Medicine, 1993; Bindman et al., 1995; Pappas, 1997; Ricketts, 2001; McCall et al., 2001; Laditka et al., 2005) categorize similar sets of ailments that can be applied to different populations with some small variations. Because the data used in this chapter include all hospital discharges in a five-year period, the annual patient population varies by age, gender, and economic characteristics. Therefore, I include a broader selection of ailments (17 general categories) than most of the current literature in order to study the relationship between physician supply and ACSC hospital admissions across different types of ACSC.

Using ACSC specification similar to the framework set forth by McCall (2001), I separate ACSC into three broad subcategories: chronic, acute, and preventable. This categorization scheme allows me to study the effect of physicians on categories containing similar ailments, rather than for the seventeen ACSC independently. Most of the chronic conditions are incurable if diagnosed, but admission to the hospital is preventable if the patient has adequate access to a PCP. The six chronic conditions include: Chronic Obstructive Pulmonary Disease (COPD), asthma, diabetes mellitus, epilepsy and recurrent seizures, congestive heart failures, and hypertension. Subcategories under COPD are characterized by irreversible airflow limitation include chronic bronchitis, emphysema, bronchiectasis, and chronic airway obstruction. Acute ACSC are normally acute manifestations of chronic ailments or acute episodes of a usually treatable condition that do not require hospitalization. The eight conditions currently categorized as acute ACSC are: pneumonia (hypersensitivity pneumonitis and organism unspecified pneumonia), pulmonary tuberculosis, urinary tract infection (UTI), hypoglycemia, cellulitis, hypokalemia, ulcer, and severe ear-nose-throat infection. The last category, preventable conditions, includes gangrene, influenza, and malnutrition. These conditions usually take a long time to manifest (gangrene and malnutrition), or are usually easier to prevent hospitalization (influenza) than any acute ACSC. Although gangrene is sometimes considered as an acute manifestation of chronic diabetes type 1 or 2, this chapter uses a broader definition of gangrene that includes any tissue necrosis due to non-diabetic disease (e.g., Raynaud's, infectious organism, peripheral vascular disease, and phagedena). Higher hospitalization rates with any of ACSC listed above would suggest low accessibility to PCP or low quality of the PCP system.

Statistical studies that examine the relationship between physician supply and ACSC find mixed results. Krakauer et al. (1996) find that physician supply levels and distribution have very little influence on ACSC admission rates using linear regression models on cross-sectional data. The authors also find that the effect is even smaller on mortality rates, except in areas with extremely low physician supply. In the paper using similar NC discharge data, Ricketts et al. (2001) find there is no significant relation between physician primary care resources and ACSC admission rate. The only predictors of ACSC rates are income and other economic conditions in the area. Ricketts claims that adverse health outcomes are explained by the socio-economic factors in the market instead of the health care system.

Other papers find a negative relationship (Parchman et al. 1994, Laditka et al. 2005, Ansari et al. 2012) using different datasets across time and counties. Similar results are also found among the Medicare beneficiaries in both rural and urban areas (Culler et al. 1998, McCall et al. 2001). Some authors found a correlation between rurality and ACSC admissions, which they attribute to the lack of primary care access (Komaromy et al., 1996; Laditka et al., 2004).

Work by Schreiber and Zielinski (1997) reports a positive relationship between the number of physicians and ACSC. Controlling for poverty, population density, proximity to hospital and number of PCPs, Schreiber found that the number of primary care providers and proximity to a hospital are both positively associated with ACSC admissions while population density is negatively correlated with admission rates. The authors further caution against the usage of ACSC as an indicator for PC shortages in existing policies.

Overall, the findings concerning the effect of physician supply on ACSC admission rates run the gamut from a positive relationship to a negative relationship. All of the existing research falls prey to two major statistical shortcomings, simultaneity and omitted variable bias. Papers that uses Ordinary Least Squares (OLS) or generalized linear regression without considering the fact that two variables on either side of the equation would influence each other at the same time, or the flow of causality is not one hundred percent from PCP to ACSC admissions, potentially biasing the coefficients. Other papers only focus on the relationship between PCP and ACSC without considering characteristics in the area that affect both the supply of physicians and the patient demographics. To address these issues, I attempt to control for unobserved heterogeneity through the RD method and by including a broader range of county-level characteristics.

3.3 Existing Policies

In the 1950s and 1960s, migration of rural physicians into urban areas, combined with increasing specialization among physicians decreased the PCP supply in the US, especially in rural areas. The US Congress created the Health Professional Shortage Area (HPSA) indication and the National Health Service Corps (NHSC) in the 1970s to easily and clearly identify areas in need of physicians and other health professionals in order to address the physician shortage problem. To be considered a HPSA, an application with reasons for the request, accompanied by data, must be sent to the Health Resource and Service Administration (HRSA).

There are three classifications of HPSA designation for different types of physician shortages: primary medical care, dental, and mental health. Within each HPSA, shortages can be sorted into three categories: geographic areas, population groups, or facilities. For this chapter, I use the designation of whether or not a county exhibits PCP shortage by geographic area because ACSC admission is measured at the hospital level from inpatient data. I do not use shortages by population because this designation generally captures access barriers that prevent certain population groups from using medical services, which is difficult to capture using existing county-level data.[3] I also do not use the facility designation of HPSA because, for facilities to receive HPSA, they have to be a Federal or State Correctional Institution with a particular number of inmates or a non-profit facility such as a migrant health center. The mechanisms behind population and facility HPSA are different from the effect this chapter is trying to measure.

For a county to be assigned primary care HPSA, the physician to population ratio in the county must be lower than 1:3500. The threshold is strict with one exception. Any county that exhibits high need can request a lower threshold of 1:3000. High need designation is assigned if at least one of three criteria are met: the area has more than 100 births per year per 1,000 women of child-bearing age, the area has more than 20 infant deaths per 1,000 live births, or the area is one in which more than 20 percent of the population have incomes below the poverty level.

The timing of HPSA designation assignment and retraction depends on the amount of backlog and processing time at both the state and federal levels. An inquiry to offices in charge of North Carolina and federal HRSA reveals that the assignment requires reconciling the submitted application with data from the census bureau and physician licensure data. However, additional checks might be performed by phone and in person if needed. Therefore, confirmation of HPSA assignment ranges from less one month to years. Although requests for HPSA assignment are normally initialized by the county, there have been incidences where the state HRSA gives the HPSA designation to counties that have not applied but show need consistently.

For areas recognized as an HPSA, the NHSC agency would provide both job opportunities and loan repayment for physicians who are willing to relocate to these areas and provide service. The first clinician was placed by NHSC in 1972 and, since then, more than 30,000 clinicians have served in the Corps. According to the report published in 2012 by the Community Health Councils (CHC), more than 7,500 clinics and 10,000 sites currently participate in the program, serving over 7 million patients across the United States.[4]

For medical students in their final year of medical school, NHSC's Students to Service Loan Repayment Program (S2S LRP) provides a tax-free award up to $120,000 to medical students (MD and DO) for a commitment to provide full-time primary health care for at least 3 years or part-time for at least 6 years at an NHSC-indicated

[3]HRSA defines barriers to access as economic, linguistic, cultural, architectural, or refusal of some provider to accept certain types of patients or to accept Medicare/Medicaid payments.

[4]http://chc-inc.org/downloads/PB/20HPSA/20Guide/2010-08-12.pdf

HPSA of greatest need. Physicians continuing to work in those areas after completion are eligible for more loan forgiveness. PCPs who already have a board license can get up to $50,000 to repay their loan through the NHSC Loan Repayment Program in exchange for a two-year commitment. NHSC also provides a scholarship to current medical students for each year of financial support (up to four years) if the student agrees to serve one year (minimum two years in total) in an HPSA.

The loan repayment programs are only available to U.S. citizens or U.S. nationals, but there are other policies initiated by the US to draw foreign physicians to underserved areas through the Department of Health and Human Service (HHS), the Department of State (DOS), and the U.S. Citizens and Immigration Service. A foreign physician who currently on a J1 visa or exchange visitor classification, who is interested in serving in an HPSA, can apply for an extension of the J1 visa (or be granted a waiver of the J1 visa two-year foreign resident requirement). A J1 visa extension allows for a longer stay in the U.S., so a foreign physician has more time to acquire a Green Card or US permanent residency. The foreign resident requirement waiver allows them to adjust their status (J1 to permanent residency) without leaving the country. Both policies are extremely attractive to foreign physicians and have increased the number of foreign physicians in the US after their implementation.

The retraction process of HPSA designation is always initialized by the Secretary of Health and Human Services in the form of a formal letter to the county's primary care office (PCO). The county is then allowed 60 days to counter the retraction of the HPSA designation. If no additional evidence is presented, the county loses its HPSA designation and respective benefit. In North Carolina, the retraction process is initialized by the state on all HPSA areas every three to four years. However, retraction depends on the amount of backlog and when the county first applied for the designation. No new assignment or retraction is performed when the database is updated in NC, the timing of which is determined randomly by the state government. The new system should be completed in June 2017. The new system should decrease the time between checks and retraction to no more than three years.

Based on publicly-available information provided by the state and federal departments in charge of HPSA designation, both assignment and retraction require coordination between the state and federal government, which may depend on random, non-HPSA events. While initiation and retraction are prompted by a countys proximity the PCP-to-population threshold, the timing of the actual designation (i.e., which determines program availability) is exogenous.

3.4 Data and Summary Statistics

In the following section, I describe the datasets used for estimation: the North Carolina Hospital Discharge data, the Physician Licensure Database from the North Carolina Medical Board, and the aggregate county database-Log Into North Carolina (LINC). Databases are merged using zipcodes, which I aggregate to the county-level. As noted by Ricketts (2001), North Carolina is a diverse state with a relatively equal distribution of urban and rural counties across its 100 total counties. The ability to link the entire inpatient population and the physician population by zipcode provides us an opportunity to explore the relationship between primary physician supply and ACSC admission rates by patient demographics over time.

3.4.1 Inpatient Hospital Discharge Data (Patient-Level Data)

The annual hospital discharge data for inpatient services are collected by Truven Health Analytics (Truven) from all NC hospitals. This chapter uses data from 2003 to 2007. Variables included in the data are patient origins, patient characteristics, total days spent in the hospital, physician diagnoses, procedure performed, cost, and discharge status. Among the patient origins variables, I use patient self-reported residence zipcode to determine from which county the patient originates and the distance to the hospital of admission. Patient characteristics such as age, gender, race, ethnicity, and insurance are used to stratify the sample group for analysis. Table B.9 displays the demographic breakdown of all patients in NC over time, with a total of 5,481,258 patient-year observations. Discharges of patients from the hospital are broken down into multiple categories, where around 75 percent are discharged to home, self or outpatient care, 12 percent are transferred to a facility that provides nursing, custodial or support care, and three percent expired during their stay.

In the discharge data, patients can receive up to nine diagnoses from physicians. The first diagnosis code is an optional admission diagnosis whereby a physician diagnoses the patient based upon medical information from their prior location or makes an on the spot diagnosis when the patient is admitted. The other eight diagnoses are made after the patient is admitted. All diagnoses used in this chapter are from the International Statistical Classification of Diseases and Related Health Problems, or usually called by the short-form name International Classification of Diseases (ICD) codes, not the Diagnosis-related group (DRG). For the data in this chapter, an older version of the ICD-9 code is used instead of ICD-10 to keep the data uniform. Using the ACSC classification outlined by McCall (2001), Table B.1 displays the breakdown of ICD-9 codes for all ACSC ailments. Patients with any diagnosis that falls under the ICD-9 codes is counted toward the final counts of ACSC occurrences. The total number of ACSC over time is listed in Table B.3, broken down into five categories: ACSC, chronic, acute, preventable, and multiple. ACSC indicates that the patient exhibits at least one ailment, while the next three categories (chronic, acute, preventable) are subcategories of ACSC. The last group, multiple, means the patient exhibits at least two of the three subcategories. The table also separates the ailment groups by patient county of origin: rural or urban. As expected, the population adjusted ACSC ratio is significantly higher for rural areas than for urban areas. Tables B.5 and B.7 break down the average cost and days stayed. On average, most ACSC exhibit a higher cost and longer hospital stay than non-ACSC.

3.4.2 Physician Licensure Database (Physician-Level Data)

The North Carolina Physician Licensure Database from the North Carolina Medical Board provides annual physician-level data from 2003 to 2012. The data are collected and released by the North Carolina Health Professions Data System (HPDS). The database tracks the universe of physician applications for NC medical licenses, which must be renewed annually. It provides a comprehensive view of the physician labor force in the state and allows a researcher to track the movement of all physicians within the state over time.

Prior to May 2009, the state allowed two methods for annual license renewal: paper and electronic. Complicated to process and prone to mistakes, paper applications have been phased out in favor of an electronic renewal process on the NC Medical Board website. Because medical licenses are time delimited, the Board sends a renewal notice two months before each physician's deadline (dated as his/her birthday). On average, the electronic renewal process takes about 15 minutes because the information regarding education history, demographics, and work history often remains unchanged. If a physician changed location of practice, facility type, or specialty, they must update this information. Many physicians also provide updates when they decide to become inactive, by indicating retirement or other reasons. Inactive physicians that annually update their status can avoid a time-consuming reinstatement process should they decide to return to practice.[5]

If a physician fails to renew the license on time, a grace period of 30 days is provided and the physician is charged an additional late fee. If renewal is not completed during the grace period, the license is placed on inactive status and it is illegal to practice medicine or surgery, write prescriptions or administer prescription drugs in NC under any circumstances. If the inactivity period is less than one year, it is necessary to pay an additional fee and undergo a background check to reactivate the license.

However, if there has been an interruption in the continuous, clinical practice of medicine greater than two years, the applicant may have to reestablish his or her competence to practice medicine safely to the Board's satisfaction, in accord with GS 90-14 (11a). The reinstatement procedure might entail, and is not limited to, full-scale assessments, engagement in formal training programs, supervised practice arrangements, formal testing (Board Examination), or other proofs of competence. The Board is much more likely to require a physician who has not maintained annual notification of reason for inactivity to undergo these competency procedures.[6] Such

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[5]Among physicians who become inactive by notifying the board, rather than failure to renew, the four most common reasons are: primarily engaged in medical research and/or teaching, employment in a non-medical field/industry, temporarily out of the labor force, and retirement.

[6]Updated requirements for medical license renewal process comes from the North Carolina Board of Medicine: http://www.ncmedboard.org/renewals/renewal_type/category/physicians.

decisions are made on a case by case basis.

After a physician submits his/her application, the information is processed and updated in HPDS. Basic information in the database includes an ID number to identify the physician through time (not the board license number), gender, race, age, medical school, internship, residency, location of practice, facility type, and practice specialty.

In total, there are 166 specialties recorded in 2003 and a total of 55 additional specialties were added throughout subsequent years of observable data. Areas of expertise that fall under PCP labor supply, which is the focus of this chapter, include family medicine, general internal medicine, general pediatrics and general OB/GYN. The broader inclusion of PCP follows the guideline set forth by the AMA. Only full time (35 hours+ weekly) PCPs who deal directly with patients are counted toward PC physician supply. Table 2.6 reports the numbers of PCPs in the data sample in rural and urban counties. As expected, there are significantly more physicians in urban areas than rural areas. Perhaps even more surprising is the fact that there are rural counties in NC that are consistently without any PCPs.

3.4.3 Log Into North Carolina (County-Level Data)

I obtain county-level data from Log Into North Carolina (LINC), which combines census data from both state and federal agencies. The 100 counties of NC differ greatly in wealth, size, and the demographics of its residents. I link the county-level data with the location of the physician's primary practice. The county-level data include basic demographic variables that summarize the size, age, and race distributions of the population in each of the 100 counties in NC. These variables include the number of unemployed, income per capita, total retail sales, and number of industry establishments. Importantly, the county-level variables also include characteristics of the medical care market in the county. The variables chosen reflect the potential demand for medical care as well as medical care supply-related characteristics (i.e., number of hospital beds, number of long-term care beds, and total number of Medicaid eligible and Medicare enrollees). Summary statistics for available county-level data are provided in Table B.11 are averaged over the 100 counties by year. [7]

3.5 Theoretical Model

3.5.1 Individual's Problem

Consider a simple model, where the health (H_{ij}) of individual i in county j is determined by the number of visits to a PCP (V_{ij}), individual's characteristics (X_{ij}), and unobserved (to the econometrician) characteristics (ϵ_{ij}). Specifically,

$$H_{ij} = \alpha_0 + \alpha_1 V_{ij} + \alpha_2 X_{ij} + \epsilon_{ij} \tag{3.1}$$

[7] All dollar-valued variables are adjusted to reflect real values in year 2003 dollars.

Taking the number of PCPs serving her area as a given, an individual's demand for PCP visits depend on the number of PCPs serving county j (PC_j), individual characteristics (X_{ij}), health (H_{ij}) and unobservables (ϑ_{ij}). Visits to PCPs captures the interactions between physicians and patients because the existing literature uses ACSC admissions to capture access to PCPs.

If the health of the individual falls below a particular threshold, $\overline{H}$, I assume she seeks treatment at the hospital (i.e., she is admitted or $A_{ijt} = 1$). I assume an individual places a high value on life (versus death) and would always go the hospital if $\overline{H}$ is reached. Additionally, I assume that a hospital always treats a patient regardless of the health condition at the time of admission.

Furthermore, following a particular distributional assumption about health (i.e., $H_{ij} \sim F(\cdot)$), the probability of health falling below the threshold is denoted by $\pi_{ij} = f(H_{ij})$. The probability of going to the hospital is decreasing in V_{ij} until some unknown threshold ($\frac{\partial \pi}{\partial V} < 0$). In contrast to no treatment, a PCP is more likely to detect an ailment and to provide treatment that deters or prevents a more severe manifestation of the disease. However, the marginal benefit of visiting PCPs decreases over time.[8] For example, an annual medical examination is deemed beneficial by the American Medical Association and the American public with 92 percent of Americans believing it to be an important part of their health care (Bloomfield, 2011; Kaiser Health Tracking Poll, 2014), but the marginal benefit of PCP visits decreases as the number of visits increases.

Mathematically, the above concept can be formalized as:

$$\begin{aligned}
\pi(H_{ij}) &= \mathbb{P}[H_{ij} \leq \overline{H}] \\
&= \mathbb{P}[\alpha_0 + \alpha_1 V_{ij} + \alpha_2 X_{ij} + \epsilon_{ij} \leq \overline{H}] \\
&= \mathbb{P}[\epsilon_{ij} \leq \overline{H} - \alpha_0 - \alpha_1 V_{ij} - \alpha_2 X_{ij}] \qquad (3.2)
\end{aligned}$$

If the individual is above health threshold, the only cost is the cost ($\underline{c}$) of going to a PCP, where the cost per visit is homogeneous. However, if the individual experiences any ACSC episode $H_{ij}^B \equiv H_{ij} < \overline{H}$, an additional cost, $\overline{C}$, is incurred.

Because an individuals utility depends upon the amount of the consumption goods and the individuals health, the individual selects the number of PCP visits to maximize expected utility subject to a budget constraint that incorporates the expenditures on the consumption goods and PCP visits along with the potential cost of hospital care if the individuals health declines below $\overline{H}$. To formalize the concept, individuals select the optimal number of doctor visits V_{ij} to maximize their utility function U_{ij}, subject to a budget constraint where I_i is the total

[8] Hypochondriacs are examples of overconsumption of PCP care.

income earned at any period which is used to pay for PCP visits ($\underline{c}$) as well as hospital visits ($\overline{C}$) if health drops below the threshold $\overline{H}$:

$$\max_{V_{ij}} U_{ij} = h(H_{ij}, C_{ij})$$
$$\text{subject to } I_i \geq g(C_{ij}, \pi_{ij}, \underline{c}, \overline{C}) \tag{3.3}$$

The number of hospital admissions for ACSC, which the econometricians observes, is aggregated at the count-level, $\sum_j A_{ij} = A_j$. The number of ACSC admissions is indirectly affected by the number of PCPs in the county where the population is treated. The function $g(\cdot)$ is a generic function of $C_{ij}, \pi_{ij}, \underline{c}, \overline{C}$ that defines the relationship between income, consumption, the probability of health falling below the threshold, the cost per PCP visit, and the hospital cost if health falls below the threshold.

3.5.2 PCP Problem

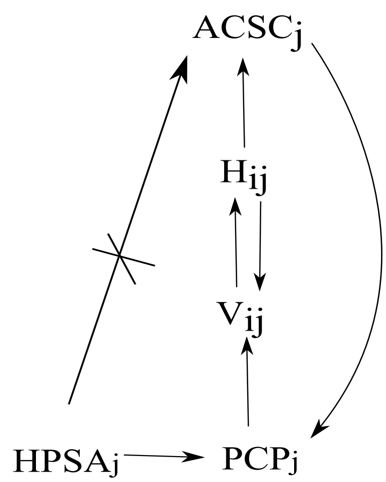
The physician chooses their location of practice (j) based on county-level characteristics, the number of hospital admissions (A_j), available government policy (G_j), and an unobserved component (ψ_{ij}).

$$\max_j U_{ij}^{PC} = p(X_{ij}, A_j, G_j, \psi_{ij}) \tag{3.4}$$

Government policy (G_j) refers to the HPSA designation given to counties that exhibited the need for PCPs. If $G_j = 1$, or the HPSA designation is in effect, then the county receives a physician if there are physicians and funding available. This indicator is important in the empirical framework because it allows the model to correctly identify the effect of physician supply on patient outcomes as measured by ACSC admissions.

To visualize the intercorrelated relationship between the patients and physicians, Figure 3.1 shows a simple theoretical relationship between ACSC admissions, the number of PCPs and government policy aimed at changing physician supply.

Figure 3.1: Graphical Representation of the Model



3.6 Empirical Model

3.6.1 HPSA designation and its Significance

Before I present the empirical model that assesses the causal effect of PCP supply on ACSC admissions, I need to first address the government assignment and retraction of the HPSA designation and its exogenous effect on the PCP supply at the county-level.

Although the state and federal government use the PCP-to-population ratio to determine whether a county is a HPSA; the timing of the granting and removal of HPSA designation has been under scrutiny (especially the removal process) in recent years. Since the HPSA withdrawal process is always initiated by the Secretary of Health and Human Services (or an officer of similar position and power) through written notice to the county, a county with higher than the threshold level PCP-to-population could fly under the radar if the government did not initiate the process. Because the state government initiation of the withdrawn process is random, these counties continue to enjoy the extra resources for PCPs. On the other hand, for counties below the HPSA threshold that have submitted an application, the assignment timing for them is also random due to backlog and the application process.

Since assignment and retraction can occur at any time during the year, a county is considered to have an HPSA designation if and only if the designation has been in effect for more than six months in any given year. For example, if county j receives HPSA designation in October of 2003 but the status was retracted in April of 2005, HPSA designation is only in effect for 2004 in my analysis but not for 2003 or 2005. This is due to the nature of the funding process of HPSA because a county with an active HPSA status would not immediately receive funding and would not receive any funding for at least 2 months before the actual retraction occurs.

The true HPSA designation date is constructed from data listed on the HRSA database,[9] while the true shortage designation is constructed from the PCP-to-population threshold from county-level data.[10]

To demonstrate this exogenous assignment and retraction, Table 3.1 shows that out of all year-county observations, about one-quarter of counties that have a PC shortage according to the PCP ratio did not receive the HPSA designation in the 2002-2007 period, i.e., the sample period.[11] Additionally, about one-quarter of counties that do not show a shortage are designated as HPSAs. Therefore, there are errors (or delays) in both government assignment and retraction of the HPSA designation. In addition, of areas that have an HPSA designation, around 90 percent of have had the HPSA designation in previous periods.[12]

Table 3.1: Government HPSA vs. True PCP Shortage Counties from Data

2002-2007	HPSA	Not HPSA
Data-PCP Shortage	45	14
Data-No PCP Shortage	129	412

3.6.2 Fuzzy Regression Discontinuity Design

Consider an equation characterizing the causal relationship between PCPs, $PCP_{j,t}$ and ACSC admissions in county j at time t:

$$ACSC.Count_{j,t} = \alpha_0 + \alpha_1 PCP_{j,t} + \alpha_2 X_{j,t} + \nu_{j,t} \tag{3.5}$$

Equation 3.6 controls for other county-level characteristics $X_{j,t}$ and idiosyncratic error $\nu_{j,t}$. Estimation of the above equation using OLS with and without county-level characteristics may lead to biased estimates of α_1 because physicians may be demand-driven agents that locate in areas with high ACSC presence.

Control variables are included in the equations, $X_{j,t}$, capturing the county-level characteristics from the

[9] To my knowledge, data on the effectiveness of the program and the number of physicians drawn into under-served counties is not available.

[10] Similar to the process used by the state and federal government, I use Census data as well as state-collected databases to construct the shortages areas.

[11] A similar comparison is performed for the time period between 2002-2012 and the result are the same.

[12] Table B.16 shows the county characteristics for counties below the physician shortage threshold of 1:3500 with and without HPSA designation. Between the two types of counties with and without HPSA designation errors, there is no statistically difference between county characteristics at the one percentage level. This means that counties below the HPSA threshold have the same observable characteristics and HPSA designation is random due to different barriers, such as bureaucracy, timing, and/or unexpected press releases.

patients region of residence such as the number of short-term care beds (i.e., hospital beds), number of long-term care beds (i.e., nursing home beds), number of Medicare eligibles, number of Medicaid enrollees, per-capita income, poverty level, rurality designation, and population demographics.

As described in the sections above, the HPSA designation should significantly increase the number of PCPs on the county-level at the 1:3500 PCP-to-population cutoff, c. A way to address the simultaneity bias between PCP supply and ACSC admissions is through the RD design. The identifying assumptions in my analysis are that all other outcome-determining characteristics except for the number of PCPs and probability of HPSA designation vary smoothly near the cutoff and that the outcome of interest, ACSC admissions, changes at the cutoff only because of the induced change in PCP supply. The following section describes and tests the validity of the identifying assumptions for this method (Trochim 1984; Hahn et al. 2001).

The advantage of using RD is that the method allows me to uncover the causal effect in a quasi-experiment framework by comparing observations on either side of a cutoff from an exogenous intervention. Theoretically, the policy implemented by the government increases the number of physicians at the cutoff, which in turn decreases the number of ACSC admissions. Since HPSA designation is given by the government at a PCP-to-population level and assignment and retraction has errors, the jump in the probability of receiving the treatment ($G_j = 1$) at the cutoff is less than one. This means that the probability of government HPSA assignment does not jump from zero to one at the cutoff, this is a "fuzzy" regression discontinuity, which is similar to a variation of the Instrumental Variable (IV) approach (Imbens and Lemieux, 2008). The basic idea for IV is that the observed values of $PCP_{j,t}$ can be replaced by predicted values of $PCP_{j,t}$ that are related to the dependent variable but uncorrelated with the error term.

The forcing variable used in my RD is the number of physicians in the data, and the threshold is defined as whether or not the county should receive government assistance base on this data, $\overline{PCP}_{j,t}$. It varies at the county-level because the number of threshold physicians increases as population increases and vise versa. The dummy $Z_{j,t}$ measures the whether the county is a shortage area, where $Z_{j,t} = \mathbb{1}(PCP_{j,t} - \overline{PCP}_{j,t})$. Since the HPSA indicator from the government depends on both the number of physicians and population, both variables are used in the model.[13] The equations estimated in the RD frame work are:

[13] A different model specification with a contemporaneous policy effect ($Z_{j,t}, G_{j,t}, PCP_{j,t}$) is also estimated, but for simplicity only the empirical model with the lagged policy effect is shown for brevity in this section.

1st Stage:

$$G_{j,t-1} = \alpha_0 + \alpha_1(PCP_{j,t-1} - \overline{PCP}_{j,t-1}) + \alpha_2 Z_{j,t-1}(PCP_{t,j-1} - \overline{PCP}_{j,t-1}) + \alpha_3 Z_{j,t-1} + \alpha_4 X_{j,t-1} + \phi_{j,t-1} \tag{3.6}$$

2nd Stage:

$$PCP_{j,t} = \beta_0 + \beta_1 \widehat{G}_{j,t-1} + \beta_2(PCP_{j,t-1} - \overline{PCP}_{j,t-1}) + \beta_3 Z_{j,t-1}(PCP_{t,j-1} - \overline{PCP}_{j,t-1}) + \beta_4 X_{j,t} + \mu_{j,t} \tag{3.7}$$

3rd Stage:

$$ACSC_{j,t} = \gamma_0 + \gamma_1 \widehat{PCP}_{j,t} + \gamma_2(PCP_{j,t-1} - \overline{PCP}_{j,t-1}) + \gamma_3 Z_{j,t-1}(PCP_{t,j-1} - \overline{PCP}_{j,t-1}) + \gamma_4 X_{j,t} + \varepsilon_{j,t} \tag{3.8}$$

where, $G_{j,t-1}$ is the lagged government HPSA designation in county j, $Z_{j,t} = \mathbb{1}(PCP_{j,t} - \overline{PCP}_{j,t})$ or an indicator variable which denotes whether or not county j is below the PCP-to-population threshold, $X_{j,t-1}$ is the list of lagged county characteristics, and $X_{j,t-1}$ is the list of contemporaneous county characteristics.

In order to accurately capture a causal interpretation of the RD design, the non-confounded assumption is required. This assumption means that a county cannot manipulate the data in order to receive an HPSA designation and its corresponding funding. Because the government has to evaluate their own data when assigning HPSA status to counties, the number of physicians and the population in the area is accurate regardless of the county of application. In addition, I perform graphical analyses to test the validity of using RD. As shown through the scatter bin diagrams (Appendix Figure A1-5), there is a clear break at the threshold $\overline{PCP}$, but there is no relationship between the forcing variable and other covariates.

3.7 Results

To substantiate the claim that previous research recovers biased estimates of PCP supply on ACSC admissions, I use the sample data to compare the results from univariate OLS (physicians only), multivariate OLS (includes county-level controls), and the RD method in Table B.12. Similar to the existing literature, the results are mixed across different methods. The coefficients for the univariate OLS are positive and significant in levels. Although adding additional independent variables and controlling for omitted variable bias decreases the positive bias of the coefficient, the coefficients are insignificant in multivariate OLS. The only results that are significant and negative (the theoretically expected result) are from the RD method. Table B.13 shows results from the RD regression with covariates from all stages. Table B.14 further break down the categorization of ACSC into chronic, acute, preventable and multiple conditions using RD. Additional analyses by age group, race and gender are also performed to examine the heterogeneous effect of PCP on ACSC admissions.

Looking at Table B.13, the results from the RD model display a significant negative relationship between PCP supply and ACSC admissions. A one unit increase in PCP decreases ACSC admissions by almost 148 incidences. This means an additional PCP, or an average of 3.5 percent increase in rural PCP supply, decreases ACSC admissions by 4.2 percent on average in rural counties. In the first stage, the coefficient of the true shortage indicator derived from PCP supply and population is significantly positively correlated with the HPSA designation by the government but is less than one. This further substantiates the usage of "fuzzy" discontinuity design because if a county is below the cutoff, the county is more likely to be a HPSA. In the second stage, there is a significant positive relationship between the HPSA designation and the number of PCPs, more specifically, a county with a HPSA designation at the threshold would have four more PCPs than its non-HPSA counterpart.

There is also a significant positive relationship between numbers of short-term care beds and ACSC admissions. Short-term care beds or hospital beds are an important control as the number of beds providing the opportunity for patients to be treated, which leads to the positive relationship. However, the indicator variable for whether or not the county is urban or rural is not significant in our analysis. Similar to what Rickett found in his paper, whether or not a county is rural or urban does not significantly affect the number of ACSC. Holding economic characteristics such as per capita income and number of people below the poverty level constant, a rural county does not differ greatly from an urban county in terms of preventable hospitalization.

Examining subcategories of ACSC, Table B.14 shows that PCP supply has the largest effect on chronic ACSC while the effect is the smallest and insignificant with preventable ACSC admissions. Because patients with chronic conditions require more frequent outpatient care in order to maintain their health, easy access to a PCP prevents more ACSC admissions for those at-risk patients than for the rest of the population. Since preventative care is more dependent on the patients willingness to care for themselves, the effect of additional PCPs is small and insignificant on preventable ACSC. This result means that treatment for preventable ACSC and the corresponding patient welfare is not dependent on the access to PCPs. Comparing the models with lagged and contemporaneous policy, it is evident that lagged policy has a stronger effect on ACSC admissions because it allows the county more time to increase its PCP supply. Thus, a county with a longer HPSA duration is able to attract more physicians and decrease the number of ACSC admissions by a larger magnitude across all types of ACSC.

Since prior research has shown that ACSC affects patients differently across their lifecycle, I divided the sample into five age groups: pre-adolescent (age 0-18), adult (age 19-39), prime age (age 40-64), post-retirement (age 65-84), elderly (age 84+). As seen in Table B.15, the effect of access to PCPs on ACSC is more prominent in the prime age and post-retirement age group. This finding is very different from other papers. The result is logical, however, because aging adults are more vulnerable to limited access than their younger counterparts since their failing health makes them more prone to be admitted to the hospital for ACSC.

When comparing the effect of physician supply across genders (shown in Table B.15), I find females benefit more from an increase in PCPs than their male counterparts in ACSC admissions and its subcategories. Women may make more use of their PCPs than males. I performed some analyses by race using the same dependent variables; however, no significant differences were found. This result means that the effect of access to physicians is equally important to all races after controlling for income and other economic variables.

For robustness, I consider a window of data symmetric about the discontinuity to test whether the result is sensitive to the bandwidth for the first and second stages. At a small bandwidth, the estimation produces similar results and discontinuity estimates only fluctuated slightly due to the inclusion of a limited additional number of counties at the boundary. However, because the small numbers of counties below the cutoff in the data, a larger bandwidth size would render the estimation insignificant.

3.8 Conclusion

Since the creation of ACSC, many costly federal and state policies have been implemented to increase PCPs in the U.S. with the aim of improving patient welfare and decreasing preventable hospitalizations. However, the relationship between PCP supply and preventable hospitalizations (ACSC admissions) is a debated topic in the health policy literature due to the mixed empirical results. Because the number of PCPs may affect hospitalization for ACSC and physicians tend to locate in areas where there is a high incidence of these or any other illness, there is a reverse causality problem in existing studies. This chapter addresses the simultaneity problem by using timing discrepancies related to HPSA designations through RD design. Using the population of physician and patient data from North Carolina and controlling for endogeneity, I find a significant negative relationship between PCPs and number of ACSC admissions, such that an increased access to PCPs significantly decreases the number of preventable hospitalizations in NC. Estimates using different population groups indicates that female patients benefit more from access to PCP than their counterparts but the effect of PCP are the same across races. Out of the three types of ACSC patients, chronic ACSC patients benefit more from PCP presence than acute ACSC and preventable ACSC patients.

APPENDIX A

APPENDIX FOR CHAPTER 2: DETERMINANTS OF PHYSICIAN LABOR SUPPLY DYNAMICS

A.1 Results from Conditional Multinomial Logit

Although the existing migration literature focuses on both push and pull factors, my model focuses on push factors (i.e., the current location characteristics that drive physician professional and geographical decisions) with a limited set of movement alternatives. As described in the Empirical Framework of the Model section, it is possible to model the decision problem with 100 counties in NC and their respective county characteristics. However, the inclusion of individual-specific variables with county-level attributes would make the parameter space computational intractable. Another disadvantage of including push factors in the existing model is the results cannot be interpreted meaningfully in conjunction with pull factors and physicians characteristics. Although the model with all counties would produce the marginal effect of pull factors, I am more interested in the factors that drive physician to move away from a location and what types of physicians are more likely to move.

To test how pull factor and push factors affect physician decisions, I follow the random utility model, originally developed by McFadden (1974), as a baseline:

$$U_{ij} = X_{ij}\beta + Z_i\gamma_j + \epsilon_{ij} \tag{A.1}$$

where U_{ij} is the utility that individual i=1,2,,N receives from county $j = 1, 2, \dots, J$. The X_{ij} represents a $1 \times L$ vector of choice-specific attributes such as population, number of Medicare eligible in county j. The Z_i represents a $1 \times K$ vector of individual specific variables such as gender, and race. The baseline model assumes that the ϵ_{ij} follows a Type 1 Extreme value distribution. It also follows the Independent of Irrelevant Alternatives assumption (IIA) and assumes the alternatives have the same variance.

To allow for both individual level controls and county characteristics of the number of location alternatives, the model requires estimation of (J-1)*K parameters, where J is the number of alternatives and K is the number of individual level controls. This method is rarely used in a model with a large choice set and cannot accommodate a large number of controls. In my model, the location choice set is 100 counties with 1 outside option of moving outside of NC. There are more than twenty county characteristic variables and a large set of individual observed characteristics over ten year periods. There are 29,908 unique physicians in the dataset, which increases computation cost further.

Table A.1 shows the result compared with the push factors estimated without UH and with UH. Because the model does not include any individual-level controls, a majority of the coefficients are significant but may be biased. Nevertheless, the sign of the significant parameters is useful. Theoretically, the push factors should have opposite effect as pull factors, i.e., places with a higher level of undesirable characteristics would be more likely to push physicians out of the county, while counties with a lower level of the aforementioned characteristics are more likely to draw physicians in.

Out of fifteen mutually significant variables, the majority of the variables have the same sign and only three variables have opposite signs. Theoretically, physicians in high-population counties are more likely to move away than those from low-population counties, and physicians should be less likely to move to high-population than low-population counties. However, the conditional logit model shows that physicians are also more likely to move to counties with higher populations. This contradictory result could be due to the exclusion of individual characteristics and simultaneity bias, i.e., areas with higher population would attract more physicians and see more physicians leaving as well.

To address this issue and avoid inclusion of a unfeasibly large set of parameters, I included only two sets of individual-specific variables, gender and race. Table A.1 compares the results with the push factors estimated without UH and with UH. The number of the mutually significant variables with opposite signs increases, where a majority of the variables in the second model have opposite signs (3 variables out of 16 have the same sign).

I attempt to add in more individual-level characteristics but it is infeasible. The existing results demonstrate that the conditional logit with only county-level controls tends to be biased, but the inclusion of several individual characteristics does improve the results. The mixed logit model demonstrates that pull factors tend to have the opposite effect on physician location decisions as push factors. For computation simplicity, I include only push effects in my model estimation.

Table A.1: Conditional and Mixed Logit Comparison

	Conditional Logit with No Exog. Variables	Conditional Logit with Exog. Variables	Multinomial Logit without UH	Multinomial Logit with UH
	Coeff.	Coeff.	Coeff.	Coeff.
Births (1000s)	0.66***	0.80***	-0.54***	-0.54***
Gross Retail Sales (Billion $)	0.02***	-2.45***	0.25***	0.26***
Hospital Discharges (1000s)	-0.04***	-0.01	-0.01**	-0.01**
Acute Care/Hospital Beds (100s)	0.002	0.34***	-0.12***	-0.13***
Population (10,000s)	0.06***	-0.07*	0.05***	0.05***
Midlevel Practitioners	-0.00	-0.05***	0.00***	0.00***
Registered Nurses (1000s)	0.60***	-0.25**	0.19***	0.21***
Long-term Care/Nursing Home Beds (100s)	0.08***	0.10***	-0.06***	-0.07***
Medicaid Eligibles (10,000s)	-0.03***	-0.66***	-0.14***	-0.15***
Medicare Insured (10,000s)	-0.03***	1.47***	0.01	0.02
Unemployed (100s)	-0.00***	0.02***	-0.00***	-0.00***
Pregnancies (100s)	0.06***	0.10***	0.04***	0.04***
Per-capita Income (10,000 $)	-0.35***	0.49***	-0.09**	-0.1**
Industrial Establishments (100s)	-0.02***	0.10***	-0.03***	-0.03***
Older Population (65+) (1,000s)	0.020***	-0.13***	0.06***	0.06***
Local Education Expenditures (10 Million $)	0.03***	-0.42***	0.03**	0.04**
Total Education Expenditures (10 Million $)	0.05***	-0.43***	0.04***	0.04***
Public School Personnel (100s)	0.06***	-0.19***	-0.05***	-0.05***
Public School Personnel with MA (100s)	-0.05***	-0.13***	-0.01	-0.01
Average SAT Math (100s)	-0.11***	-0.62***	-0.13	-0.06
Average SAT Verbal (100s)	-0.39***	-0.05	0.12	0.07

A.2 Location and Rurality Construction

In the licensure renewal process, each active physician provides the address of his/her primary location of practice. Physicians can also provide location of secondary or tertiary practice, business, and home. Valid zipcodes that are not between the smallest zipcode in North Carolina (27006) and the largest zipcode in North Carolina (28909) are coded as outside of NC. If primary location is missing, I intelligently assign a location based on other information in the data. If available, the business zipcode replaces missing observations of primary location of practice. For remaining missing primary zipcodes, where facility type is provided and unchanged between years, primary location in the previous year replaces the missing value. Home zipcode is used to fill in the remaining missing values. In some cases, the primary location zipcode is missing but the facility type is the same as the type listed in the secondary location that has a zipcode. In these cases, I use the secondary zipcode to fill in the primary location. Remaining observations that are missing are not included in the estimation sample. Only 2,518 unique physicians remain which are missing the primary location of practice and cannot be intelligently filled in. These missing observations are not included in the research sample.

The Sheps Center and Rural Center of NC have a clear definition of rural or urban counties. However, there is another way to categorize urban and rural designation through the usage of zipcodes instead of aggregating the zipcodes to the county level. There are around 850 zipcodes in NC, which physicians can select as their primary location alternative. One advantage of using zip codes to separate rural from urban areas is the precision it gives to the model. A county contains multiple zip codes but the number of zipcodes within a county varies greatly, as the largest county by population (Mecklenburg County) covers around 83 zip codes, while the largest county by landmass (Robeson County) covers only 17 counties. Even within counties of the same rurality designation, the number of zipcodes included differ in both population and landmass. Orange County, an urban county with average landmass size, has only 9 zip codes. In all counties, regardless of its rurality designation, there are zip codes that are densely populated while some are sparsely populated. It is likely that physicians that serve in rural counties tend to concentrate in more populated areas. Thus, the marginal effect of county characteristics on physician geographical and professional decisions could be different between a physician in a densely populated zipcode and a physician in a sparsely populated zipcode conditional on the same county rurality type. Therefore, a physician in a high-density populated area with a rural designation might behave similarly to a physician in a high-density populated area with an urban designation than his/her rural counterparts in low population zipcodes.

Although there are multiple definitions of rurality from multiple government agencies, the most commonly used one is the Census designation, where the agency categorizes area to either Urbanized Areas (UAs) or

Urban Clusters (UCs) and all other areas that are not urban is considered rural.[1] This definition is applied to cities or metropolitan statistical areas (MSAs).[2] Because the Census does not provide the border for each urban city/MSA, the designation is broad and geographically vague. Three additional definitions of rurality are provided by the Economic Research Service (ERS) from the United States Department of Agriculture (USDA): Rural-Urban Continuum Codes, Urban Influence Code, and Rural-Urban Commuting Area (RUCA). The first two indices are on the county-level, and only the last one is based on zipcode. Like the MSAs, the RUCAs are based on Census data that assigns a code to each Census Tract. Tracts inside Metropolitan counties with the codes 4-10 are considered rural. Although RUCA codes allow identification of rural census tracts in Metropolitan counties, there are some that are extremely large. In these larger tracts, the use of RUCA codes alone fails to account for distance to services and sparse population.[3] The shortcoming of the RUCA is the difficulty in interpreting the indices and the potential changes it could cause because the census tracts tend to be fluid.

To correct for the potential issues mentioned above, I construct a rural-urban index that best fit my data. Using the definition set forth by NC Rural Center as a benchmark, I sort the zip codes into rural and urban.[4] I calculate the zipcode population density by dividing 2000 and 2010 population from the NC database by the zipcode square mileage from decennial Census data.[5]

A.3 Estimation Results by Race

An additional challenge in meeting NC communities needs for physicians is to understand how the recent influx of Hispanic and Asian immigrants combined with a large existing African American presence impacts the

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[1] UAs contain 50,000 or more people while UC have at least 2,500 and less than 50,000 people.

[2] The 2010 Census listed 126 urban cities/MSA in NC, while the remaining areas are rural.

[3] In response to these concerns, FORHP has designated 132 large area census tracts with RUCA codes 2 or 3 as rural. These tracts are at least 400 square miles in area with a population density of no more than 35 people. Following the 2010 Census, the FORHP definition included approximately 57 million people, about 18 percent of the population and 84 percent of the area of the USA. However, the inaccuracy of RUCA makes it unattractive in defining zipcode rurality in my estimation.

[4] The NC Rural center definition is also used by Sheps Center. By their definition, a rural area has an average population density of 250 people per square mile or less, while an urban area has an average population density exceeding 250 people per square mile. The urban designation includes both regional city and suburban areas.

[5] The designation uses population density with land only square mileage. I evaluate the difference between indicators, there are only around 10 zipcodes out of 850 zipcodes that are different. The differences are due to the large water area, which could lead to potential underestimation if total area is used but it is too small to affect my estimation.

demand for physicians. While research has established a positive association between the number of minority physicians and health care access and patient satisfaction among minorities, existing policies have yet to address ways to facilitate the unmet needs of underserved communities regarding ethnic diversity through physician mobility. Therefore, I study the determinants of physician movement within NC by race, gender, and ethnicity of the physicians while accounting for county-level changes in demand associated with race and ethnicity.

As shown in Table 2.13, I find that African American physicians are 1.21 times more likely to change their location of practice and 0.78 times less likely to become inactive. Conditional on moving, minority physicians behave similarly to Caucasian physicians. However, they are significantly more likely to change facility in a given year and work more hours of direct patient care. One plausible explanation for the differing behavior of minority physicians is that a large minority presence increases demand for minority physicians, which results in greater hours worked and subsequently induces an employment transition. The initial relocation of some minority physicians may subsequently increase demand for the remaining minority physicians.

To explore the potential divergence in physician preferences by race, I estimate separate models for each type of physicians in two ways. For each race, the first specification includes the same variables as in the benchmark estimation. The second specification also includes the racial demographics for the physicians current county. Table A.2 displays result from the first method and compares the FIML results across race for moving within NC relative to not moving. I find Caucasian physicians are more likely to move if they report more hours of direct patient care, while Hispanic physicians are less likely to move. The coefficient for the average wage is significant for Caucasian, African American, and other physicians, but not for Asian and Hispanic physicians. Only African American physicians are more likely to move within NC if the current area is rural. The finding is partially congruent with the literature that African American physicians are more likely to move if they are in lower amenity area, but they are not less likely to be burned out through working more hours. Female African American or Asian physicians are not more likely to move than their male counterparts. Table A.3, A.4 and A.5 list results for movement and rurality outcomes across different races.

In the second model where the racial demographics enter into estimation, Table A.6 shows some unexpected results. Although a higher rate African American presence does not significantly change the likelihood of Caucasian physician movement to an urban location, a higher ratio of African Americans relative to Caucasians significantly decreases the probability of moving for African American physicians. In addition, Table A.7 shows that increase in African American population does not significantly increase per period hours of direct patient care. The finding contradicts the hypothesis that large minority presence could induce minority physician movement due to great hours work from higher demand for services. It is more plausible that African American physicians are less propense to move from an area with more African American patients or that African American patients prefer doctors of the same type as them. Due to data limitations, most of the variables are insignificant because there is a small number of other types of minority physicians.

Table A.2: Race Analysis For Moving within NC Relative to Not Moving

	White Coeff	Black Coeff	Asian Coeff	Hispanic Coeff	Other Coeff
Endogenous Var					
Moved in Previous Period	0.76***	0.92***	0.66***	0.75***	0.64***
Current Average Salary (10,000 $)	0.00*	0.00*	0.00	-0.02	-0.01**
Current Salary Rank	0.00***	0.00	0.00	0.00	0.00
Current Hours of Direct Patient Care	0.01**	0.00	0.00	-0.01**	0.00
Current Rural Location	0.00	0.35***	0.06	-0.21	0.00
Facility (relative to Group Practice)					
Solo Practice	-0.11***	-0.01	-0.12	0.18	-0.12
Hospital: ER Related	0.55***	0.41*	0.54***	0.71**	0.45***
Hospital: Non ER related	0.31***	0.27***	0.26***	0.64***	0.35*
Medical School/Parent University	-0.2	-0.18	0.03	0.48	0.04
Other Facility	0.39***	0.49***	0.21	0.13	0.36*
Specialty (relative to Generalist)					
Medical Specialist	-0.11***	-0.28***	-0.27***	-0.25	-0.18
Surgical specialist	-0.20***	-0.20*	-0.26**	-0.2	-0.26**
Hospital specialist	0.13***	-0.03	-0.08	-0.37	0.24**
Other specialist	0.37***	0.22*	0.13	-0.05	0.28*
Individual Characteristics					
Female	0.06**	0.07	0.1	0.31*	0.16**
Foreign Born	-0.04	0.03	-0.01	0.46**	0.1
Age	-0.35***	-0.49***	-0.06	-0.21	-0.28
Age Squared (divided by 100)	0.66***	1.03***	0.03	0.38	0.54
Age Cubed (divided by 10,000)	-0.39***	-0.7***	0.03	-0.21	-0.33
Experience	-0.04***	-0.06***	-0.08***	0.02	-0.05*
Experience Squared (divided by 100)	0.08*	0.06	0.33*	-0.16	0.15
Experience Cubed (divided by 10,000)	-0.01	0.18	-0.41	-0.24	-0.14
Exogenous Var					
Births (1000s)	-0.47***	-0.67**	-0.2	-1.27**	-0.83**
Gross Retail Sales (Billion $)	0.29***	0.18***	0.01	0.14	0.11
Hospital Discharges (1000s)	-0.02***	0.00	0.02	-0.02	0.00
Acute Care/Hospital Beds (100s)	-0.14***	-0.05	-0.05	0.06	-0.17***
Population (10,000s)	0.06***	0.02	-0.01	0.02	0.01
Midlevel Practitioners	0.00***	0.00***	0.00*	-0.01**	-0.01***
Registered Nurses (1000s)	0.17***	0.21	0.09	0.09	0.59**
Long-term Care/Nursing Home Beds (100s)	-0.06***	0.01	-0.06	-0.22***	-0.07
Medicaid Eligibles (10,000s)	-0.19***	-0.18**	0.09	-0.12	-0.08
Medicare Insured (10,000s)	0.04	-0.09	-0.17	-0.11	-0.28
Unemployed (100s)	0.00***	0.00	0.00	-0.01*	0.00
Pregnancies (100s)	0.04***	0.08***	0.02	0.11**	0.08***
Per-capita Income (10,000 $)	-0.1**	-0.33**	0.03	0.00	-0.23
Industrial Establishments (100s)	-0.03***	-0.03***	0.00	-0.01	-0.03***
Older Population (65+) (1,000s)	0.06***	0.06**	0.04	0.17**	0.07*
Local Education Expenditures (10 Million $)	0.03	-0.02	0.08	0.01	0.01
Total Education Expenditures (10 Million $)	0.04***	0.04	-0.02	0.03	0.07*
Public School Personnel (100s)	-0.05***	-0.03	-0.03	-0.05	-0.06**
Public School Personnel with MA (100s)	-0.01	-0.03	-0.02	-0.07	0.03
Average SAT Math (100s)	-0.24	0.39	0.23	-0.34	-0.28
Average SAT Verbal (100s)	0.11	0.11	-0.17	-0.18	0.77
Primary Care Physicians	0.00***	0.00	0.00***	0.00	0.00
Medical Specialists	0.00***	0.00*	0.00	0.00	0**
Surgical Specialists	0.01***	0.00	-0.01*	0.01	0.00
Hospital Specialists	0.00*	0.00	0.00	0.00	0.00
Other Specialists	-0.01***	0.00	0.00	0.01	-0.01**
Year	1.05***	1.35***	0.78***	0.68*	0.82***
Year Squared	-2.26***	-2.89***	-1.73***	-1.63*	-1.76***
Year Cubed	1.43***	1.82***	1.11***	1.12**	1.16***
Constant	20.85***	4.2	-0.18	4.03	69.62***

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$.

Table A.3: Race Analysis For Moving within the County to Rural Zipcode

	White Coeff	Black Coeff	Asian Coeff	Hispanic Coeff	Other Coeff
Endogenous Var					
Moved in Previous Period	1.55***	1.46***	0.89**	1.73***	1.47***
Current Average Salary (10,000 $)	-0.04***	-0.06***	-0.04**	-0.06**	-0.04
Current Salary Rank	0.00*	0.00	0.01	-0.02	0.00
Current Hours of Direct Patient Care	0.00	-0.01**	0.00	0.01	0.01**
Current Rural Location	3.75***	3.45***	4.03***	3.59***	4.18***
Facility (relative to Group Practice)					
Solo Practice	0.01	0.23	0.56	0.42	-1.06**
Hospital: ER Related	0.24	0.63*	-0.42	-0.57	0.7
Hospital: Non ER related	-0.01	-0.15	-0.17	-0.39	-0.11
Medical School/Parent University	-0.66***	-1.02*	-0.38	-1.06	-0.61
Other Facility	0.31	0.23	0.34	-2.22**	-0.26
Specialty (relative to Generalist)					
Medical Specialist	0.21	0.34	0.4	1.21*	0.24
Surgical specialist	0.21	0.47	-0.41	-0.09	0.38
Hospital specialist	0.29**	-0.45	-0.13	1.41**	-0.52
Other specialist	0.34**	-0.18	-0.69	-0.81	0.00
Individual Characteristics					
Female	0.01	0.18	-0.23	0.00	-0.16
Foreign Born	-0.11	-0.15	0.1	-0.02	0.23
Age	-0.37**	-0.21	-0.1	0.81	-0.15
Age Squared (divided by 100)	0.81**	0.22	0.16	-1.7	0.01
Age Cubed (divided by 10,000)	-0.54**	0.02	-0.05	1.21	0.28
Experience	-0.07**	-0.11	-0.21**	-0.37	0.01
Experience Squared (divided by 100)	0.09	0.73	0.88	2.33	-0.46
Experience Cubed (divided by 10,000)	0.00	-1.47	-1.13	-4.35	0.45
Exogenous Var					
Births (1000s)	0.51	-0.85	0.46	-2.32	0.55
Gross Retail Sales (Billion $)	-0.17*	-0.36	-0.01	0.22	1.08**
Hospital Discharges (1000s)	-0.11***	-0.1	-0.15*	-0.45**	-0.12
Acute Care/Hospital Beds (100s)	-0.04	0.13	-0.22	-0.12	-0.39
Population (10,000s)	0.06	-0.08	-0.16	0.75	0.24
Midlevel Practitioners	0.00*	0.00	0.01	0.00	-0.01
Registered Nurses (1000s)	0.49*	0.51	1.04	1.99	0.82
Long-term Care/Nursing Home Beds (100s)	-0.01	0.09	0.23	-0.1	0.11
Medicaid Eligibles (10,000s)	0.29**	0.61*	0.7	0.58	-0.06
Medicare Insured (10,000s)	0.11	1	-5.76***	1.64	1.02
Unemployed (100s)	0.00	0.00	0.03***	0.00	-0.02
Pregnancies (100s)	-0.07*	0.03	-0.11	-0.02	-0.16
Per-capita Income (10,000 $)	-0.79***	-1.27**	0.43	0.16	-1.89***
Industrial Establishments (100s)	0.01	0.04	0.04	-0.03	-0.09
Older Population (65+) (1,000s)	-0.12***	-0.27*	0.24	-0.21	-0.18
Local Education Expenditures (10 Million $)	0.56***	0.3	0.53	-0.03	0.65*
Total Education Expenditures (10 Million $)	-0.2***	0.04	-0.32*	0.2	0.07
Public School Personnel (100s)	0.13***	-0.02	0.5***	-0.36	-0.01
Public School Personnel with MA (100s)	-0.06	0.02	-0.45**	0.53*	0.06
Average SAT Math (100s)	-4.5***	-5.15***	1.99	-6.03*	-6.08***
Average SAT Verbal (100s)	2.79***	3.91**	-3.04	1.29	3.51*
Primary Care Physicians	0.00*	0.00	0.00	-0.01	-0.01
Medical Specialists	-0.01***	-0.02***	-0.02**	0.00	-0.01
Surgical Specialists	-0.02***	-0.02	-0.01	-0.01	0.01
Hospital Specialists	0.02***	0.02***	-0.01	0.00	0.02
Other Specialists	0.00	0.02**	0.02	0.00	0.01
Year	1.20***	-0.23	-0.42	2.26	-0.28
Year Squared	-2.55***	0.81	-0.09	-4.5	2.15
Year Cubed	1.58***	-0.51	0.39	2.42	-1.91
Constant	25.65***	17.2*	-113.74***	10.57	15.68*

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. The analysis for moving within the county to a rural zipcode relative to moving within the county to an urban zipcode.

Table A.4: Race Analysis For Moving out of the County to Urban Zipcode

	White Coeff	Black Coeff	Asian Coeff	Hispanic Coeff	Other Coeff
Endogenous Var					
Moved in Previous Period	1.64***	1.41***	1.25***	1.88***	1.32***
Current Average Salary (10,000 $)	-0.01***	-0.01	-0.04***	-0.03	-0.03**
Current Salary Rank	-0.01***	0	0.01	-0.02	-0.01
Current Hours of Direct Patient Care	0.01***	0	0.01*	0	0.01
Current Rural Location	-1.47***	-1.68***	-1.28***	-1.29**	-1.44***
Facility (relative to Group Practice)					
Solo Practice	0.1	0.13	-0.07	0.01	0.01
Hospital: ER Related	-0.34***	-0.35	0.12	0.15	0.4
Hospital: Non ER related	-0.01	-0.59***	0.2	-0.54	0.15
Medical School/Parent University	-0.18	-0.89***	-0.22	-0.77	0.29
Other Facility	0.26*	-0.43	0.78**	-1.03	0.22
Specialty (relative to Generalist)					
Medical Specialist	0.08	-0.08	-0.17	1.14**	0.5*
Surgical specialist	-0.04	0.07	0.14	-0.72	0.36
Hospital specialist	0.18**	0.12	-0.01	-0.03	-0.37
Other specialist	0.30***	0.41*	0.59*	0.2	0.49
Individual Characteristics					
Female	0.13**	0.03	-0.17	0.03	0.19
Foreign Born	0.04	-0.17	0.25	0.08	0.06
Age	-0.25**	-1.34***	-0.12	-0.29	0.11
Age Squared (divided by 100)	0.49**	2.82***	0.24	0.51	-0.38
Age Cubed (divided by 10,000)	-0.3**	-1.86***	-0.16	-0.27	0.39
Experience	-0.08***	-0.02	-0.08	0.04	-0.05
Experience Squared (divided by 100)	0.21**	-0.37	0.03	-1.48	0.04
Experience Cubed (divided by 10,000)	-0.17	0.78*	0.57	4.16	-0.1
Exogenous Var					
Births (1000s)	0.49**	1.29*	1.23*	1.6	1.25
Gross Retail Sales (Billion $)	-0.13**	-0.32**	-0.37**	-0.09	0.12
Hospital Discharges (1000s)	0.03**	0.02	0.05	-0.04	-0.01
Acute Care/Hospital Beds (100s)	0.32***	0.34***	0.46***	0.43	0.2
Population (10,000s)	-0.03	-0.08	-0.05	0.49**	0.06
Midlevel Practitioners	0.00**	0	-0.01*	0	-0.01***
Registered Nurses (1000s)	-0.76***	-0.65	-0.71	-0.67	-0.36
Long-term Care/Nursing Home Beds (100s)	0.12***	0.13	0.32***	-0.02	0.09
Medicaid Eligibles (10,000s)	-0.18**	-0.15	-0.34	0.01	-0.51*
Medicare Insured (10,000s)	-0.4	-0.69	-0.52	-0.05	1.65
Unemployed (100s)	0	0	0	0	-0.01**
Pregnancies (100s)	-0.07***	-0.16***	-0.18***	-0.23*	-0.16**
Per-capita Income (10,000 $)	-0.02	0.28	1.14***	0.84	0.1
Industrial Establishments (100s)	0.03***	0.08***	0.1***	-0.02	0.03
Older Population (65+) (1,000s)	-0.09	-0.06	-0.23***	-0.07	-0.22**
Local Education Expenditures (10 Million $)	-0.15***	-0.28**	-0.4***	0.37	-0.24
Total Education Expenditures (10 Million $)	0.13***	0.11	0.16**	-0.12	0.2**
Public School Personnel (100s)	0.01	0.02	0.08	-0.11	-0.03
Public School Personnel with MA (100s)	-0.03	-0.02	-0.09	0.13	-0.07
Average SAT Math (100s)	-3.98***	-2.87*	-4.85***	-2.27	-7.9***
Average SAT Verbal (100s)	2.56***	-0.12	1.25	-1.41	4.46**
Primary Care Physicians	0.00*	0	0	0	0
Medical Specialists	0	0	0.01*	-0.01	0
Surgical Specialists	0	-0.01	-0.03***	0	0
Hospital Specialists	0	0	0.01	0	0.01
Other Specialists	0.01***	0.02***	0.02**	0	0
Year	0.3	-0.52	0.03	0.79	1.32*
Year Squared	-0.74	0.98	-0.51	-1.99	-2.54*
Year Cubed	0.42	-0.63	0.31	1.18	1.38
Constant	14.18***	38.3***	17.86***	21.63	-37.13***

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. The analysis for moving out of the county to an urban zipcode relative to moving within the county to an urban zipcode.

Table A.5: Race Analysis For Moving out of the County to Rural Zipcode

	White Coeff	Black Coeff	Asian Coeff	Hispanic Coeff	Other Coeff
Endogenous Var					
Moved in Previous Period	0.03	-0.21	0.39	-0.9	-0.44
Current Average Salary (10,000 $)	-0.01	-0.03	-0.01	-0.07*	-0.01
Current Salary Rank	-0.01***	0.00	0.00	-0.03	0.00
Current Hours of Direct Patient Care	0.01***	0.00	0.01	0.00	0.01
Current Rural Location	1.03***	0.87**	1.25***	-0.39	0.53
Facility (relative to Group Practice)					
Solo Practice	0.06	-0.23	0.97***	-0.85	-0.52
Hospital: ER Related	-0.31*	-0.38	0.66	-3.01*	0.5
Hospital: Non ER related	0.00	0.12	0.29	-1.39*	0.26
Medical School/Parent University	0.78***	0.07	2.42***	-2.64*	1.3*
Other Facility	0.25	-0.33	0.64	NA	0.55
Specialty (relative to Generalist)					
Medical Specialist	-0.06	0.15	0.76*	2.18**	-0.05
Surgical specialist	-0.14	-0.51	0.01	0.11	0.69
Hospital specialist	-0.04	-0.18	-0.88*	1.23	-0.33
Other specialist	-0.37*	-0.43	-0.05	-0.07	-1
Individual Characteristics					
Female	-0.12	-0.3	0.03	-0.44	0.26
Foreign Born	-0.13	-0.03	0.01	0.03	0.49
Age	-0.2	-1.16*	-0.39	1.42	0.81
Age Squared (divided by 100)	0.43	2.46*	0.91	-2.64	-1.8
Age Cubed (divided by 10,000)	-0.26	-1.63*	-0.65	1.61	1.37
Experience	-0.02	0.03	-0.42***	-0.39	-0.12
Experience Squared (divided by 100)	0.00	-0.41	2.93***	3.13	1.06
Experience Cubed (divided by 10,000)	0.03	0.76	-5.7***	-6.71	-2.52
Exogenous Var					
Births (1000s)	-1.78***	-1.4	0.04	-6.36*	0.84
Gross Retail Sales (Billion $)	-0.94***	-0.36	-0.4	-0.31	0.75
Hospital Discharges (1000s)	0.04	0.01	0.19*	-0.43*	0.08
Acute Care/Hospital Beds (100s)	-0.52***	-0.15	-0.53	-0.29	0.04
Population (10,000s)	-0.37***	0.06	0.07	-0.28	0.17
Midlevel Practitioners	-0.03***	-0.01	-0.01	-0.06***	0.00
Registered Nurses (1000s)	3.31***	0.13	0.99	6.1**	1.34
Long-term Care/Nursing Home Beds (100s)	-0.47***	-0.3*	0.28	-1***	-1.12***
Medicaid Eligibles (10,000s)	0.11	0.44	-0.61	2.19**	-0.69
Medicare Insured (10,000s)	0.05	1.49	-1.08	0.62	-1.46
Unemployed (100s)	-0.01***	-0.02*	-0.03*	-0.01	-0.06***
Pregnancies (100s)	0.26***	0.02	-0.09	0.4	-0.2
Per-capita Income (10,000 $)	-1.28***	-0.86	0.33	-0.45	-0.72
Industrial Establishments (100s)	0.06**	0.11**	0.15***	0.06	-0.24**
Older Population (65+) (1,000s)	0.21***	-0.19	-0.24	0.42	0.54*
Local Education Expenditures (10 Million $)	-0.48***	-0.89***	-1.35***	-1.06	-0.89**
Total Education Expenditures (10 Million $)	0.28***	0.46***	0.35**	0.65*	0.46**
Public School Personnel (100s)	-0.22***	-0.33**	0.02	-0.11	0.05
Public School Personnel with MA (100s)	0.12	0.27*	-0.1	-0.19	0.2
Average SAT Math (100s)	-1.70**	-3.01	-2.78	-0.83	-2.69
Average SAT Verbal (100s)	1.56**	3.06	1.58	0.57	1.25
Primary Care Physicians	0.01***	0.00	0.00	0.00	0.00
Medical Specialists	0.03***	0.02	0.02	0.02	0.01
Surgical Specialists	-0.01*	0.00	-0.01	-0.04	0.05
Hospital Specialists	-0.01***	-0.01	0.00	0.03	-0.04*
Other Specialists	-0.05***	-0.01	-0.04**	-0.09*	-0.07***
Year	0.80**	-1.03	-0.08	2.49	-0.67
Year Squared	-2.13***	1.85	-0.52	-5.92	1.55
Year Cubed	1.6***	-0.97	0.6	3.81	-1.17
Constant	-0.4	24.71**	13.26	-20.93	247.86***

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. The analysis for moving out of the county to a rural zipcode relative to moving within the county to an urban zipcode. Coefficients with "NA" means there are no observation in the research sample that fits the criteria.

Table A.6: Race Analysis with County Demographics-Movement

	Move to Urban Area Relative to Not Move			Move to Rural Area Relative to Not Move		
	Coeff	SD	Odds	Coeff	SD	Odds
Caucasian						
African American Percentage	0.00	0.00	1	-0.01	0.00	0.99
Asian Percentage	-0.03***	0.01	0.98	0.01	0.01	1.01
Hispanic Percentage	0.05***	0.01	1.05	0	0.01	1
Other Race Percentage	0	0.03	1	-0.03	0.04	0.97
African American						
African American Percentage	-0.02**	0.01	0.98	-0.01	0.02	0.99
Asian Percentage	-0.02	0.01	0.98	0.01	0.02	1.01
Hispanic Percentage	0	0.02	1	0.03	0.03	1.03
Other Race Percentage	-0.15*	0.08	0.86	-0.04	0.11	0.96
Asian						
African American Percentage	0	0.01	1	-0.03***	0.01	0.97
Asian Percentage	-0.02	0.01	0.98	0.01	0.02	1.01
Hispanic Percentage	0.03	0.02	1.03	-0.03	0.03	0.97
Other Race Percentage	-0.05	0.07	0.95	-0.16	0.12	0.85
Hispanic						
African American Percentage	0.02	0.02	1.02	-0.01	0.03	0.99
Asian Percentage	0.04	0.03	1.05	0.05	0.06	1.05
Hispanic Percentage	0.06	0.05	1.06	0	0.07	1
Other Race Percentage	0.22	0.19	1.24	0	0.23	1
Other						
African American Percentage	-0.01	0.01	0.99	-0.03**	0.02	0.97
Asian Percentage	-0.01	0.02	0.99	-0.02	0.02	0.98
Hispanic Percentage	0.09***	0.03	1.09	0.06**	0.03	1.07
Other Race Percentage	-0.16*	0.09	0.85	0.03	0.11	1.03

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. All race ratio reported are relative to Caucasian percentage in the county.

Table A.7: Race Analysis with County Demographics-Hours Worked

	Hours Worked	
	Coeff	SD
Caucasian		
African American Percentage	0.00	0.01
Asian Percentage	0.00	0.02
Hispanic Percentage	-0.03	0.03
Other Race Percentage	-0.34***	0.08
African American		
African American Percentage	0.01	0.04
Asian Percentage	-0.03	0.05
Hispanic Percentage	-0.1	0.09
Other Race Percentage	-0.59*	0.33
Asian		
African American Percentage	-0.02	0.04
Asian Percentage	-0.04	0.05
Hispanic Percentage	-0.14	0.09
Other Race Percentage	-0.49**	0.25
Hispanic		
African American Percentage	0.07	0.06
Asian Percentage	0.13	0.12
Hispanic Percentage	0.11	0.15
Other Race Percentage	0.6	0.39
Other		
African American Percentage	0.10**	0.04
Asian Percentage	0.06	0.06
Hispanic Percentage	-0.17	0.11
Other Race Percentage	0.09	0.38

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. All race ratio reported are relative to Caucasian percentage in the county.

A.4 Additional Estimation Results

Table A.8: Estimation Results: Movement and Rurality Outcome at End of Period

	Move within the County to Rural Zip.				Move out of the County to Urban Zip.				Move out of the County to Rural Zip.			
	Coeff	Signif	SD	Odds	Coeff	Signif	SD	Odds	Coeff	Signif	SD	Odds
Current Average Salary (10,000 $)	-0.025	***	0.007	0.975	-0.019	***	0.003	0.981	-0.062	***	0.007	0.940
Average Salary × Rural	0.059	***	0.008	1.061	0.045	***	0.007	1.046	0.078	***	0.008	1.082
Current Salary Rank	-0.008	***	0.002	0.992	-0.005	***	0.002	0.995	-0.004	**	0.002	0.996
Current Hours of Direct Patient Care	0.006	***	0.002	1.006	0.004	***	0.001	1.004	-0.003		0.003	0.997
Experience	-0.034		0.025	0.966	-0.086	***	0.015	0.917	-0.072	***	0.025	0.930
Experience Squared (divided by 100)	0.056		0.127	1.058	0.200	**	0.082	1.221	0.127		0.122	1.136
Experience Cubed (divided by 10,000)	-0.033		0.179	0.967	-0.169		0.123	0.845	-0.103		0.168	0.902
Current Rural Location	0.256	**	0.115	1.292	-1.888	***	0.111	0.151	3.726	***	0.115	41.516
Moved in Previous Period	-0.013		0.158	0.987	1.588	***	0.078	4.892	1.544	***	0.113	4.683
Facility (relative to Group Practice)												
Solo Practice	0.095		0.115	1.100	0.059		0.078	1.061	0.015		0.116	1.015
Hospital: ER Related	-0.181		0.158	0.835	-0.099		0.092	0.905	0.342	**	0.136	1.408
Hospital: Non ER related	-0.084		0.105	0.920	-0.129	**	0.062	0.879	-0.036		0.103	0.965
Medical School/Parent University	0.531	***	0.179	1.701	-0.505	***	0.089	0.603	-0.726	***	0.176	0.484
Other Facility	0.084		0.187	1.088	0.215	**	0.108	1.240	0.359	**	0.165	1.432
Specialty (relative to Generalist)												
Medical Specialist	0.011		0.122	1.011	0.073		0.070	1.075	0.291	**	0.124	1.338
Surgical specialist	-0.114		0.124	0.892	-0.005		0.076	0.995	0.250	**	0.125	1.285
Hospital specialist	-0.108		0.120	0.897	0.110		0.071	1.117	0.251	**	0.113	1.285
Other specialist	-0.390	**	0.158	0.677	0.358	***	0.080	1.430	0.157		0.133	1.170
Female	-0.114		0.088	0.892	0.074		0.048	1.077	0.018		0.081	1.018
Race (relative to Caucasian)												
African American	0.012		0.137	1.012	0.152	**	0.074	1.164	0.087		0.121	1.091
Asian	-0.197		0.143	0.821	-0.112		0.074	0.894	-0.079		0.124	0.924
Hispanic	-0.116		0.220	0.891	-0.193		0.129	0.825	-0.066		0.231	0.936
Other Race	-0.184		0.144	0.832	-0.108		0.090	0.897	-0.184		0.147	0.832
Foreign Born	0.036		0.119	1.037	0.072		0.069	1.074	-0.012		0.118	0.988
Age	-0.178		0.174	0.837	-0.308	***	0.094	0.735	-0.368	***	0.140	0.692
Age Squared (divided by 100)	0.411		0.347	1.508	0.603	***	0.196	1.828	0.762	***	0.277	2.143
Age Cubed (divided by 10,000)	-0.265		0.224	0.767	-0.363	***	0.131	0.696	-0.480	***	0.176	0.619
County Characteristics												
Births (1000s)	-2.066	***	0.612	0.127	0.668	***	0.200	1.950	0.673		0.420	1.960
Gross Retail Sales (Billion $)	-0.373	**	0.158	0.689	-0.104	**	0.042	0.902	-0.197	**	0.087	0.821
Retail Sale × Rural	-1.034	***	0.299	0.356	-0.749	***	0.285	0.473	-0.896		0.338	0.408
Hospital Discharges (1000s)	-0.103	**	0.045	0.902	0.019		0.012	1.019	-0.044	*	0.023	0.957
Acute Care/Hospital Beds (100s)	-0.917	***	0.111	0.400	0.245	***	0.040	1.277	0.088		0.069	1.091
Population (10,000s)	-0.101	*	0.055	0.904	-0.005		0.018	0.995	0.000		0.041	1.000
Population × Rural	0.330	***	0.069	1.391	0.396	***	0.071	1.487	0.264	***	0.070	1.302
Midlevel Practitioners	-0.033	***	0.004	0.968	-0.003	***	0.001	0.997	-0.001		0.002	0.999
Midlevel Practitioner × Rural	-0.011		0.007	0.989	-0.019	***	0.007	0.981	0.004		0.007	1.004
Registered Nurses (1000s)	4.705	***	0.394	110.547	-0.450	***	0.132	0.637	0.215		0.249	1.240
Registered Nurses × Rural	-1.900	***	0.629	0.150	-0.968	*	0.543	0.380	-2.280	***	0.597	0.102
Long-term Care/Nursing Home Beds (100s)	-0.581	***	0.064	0.559	0.082	***	0.028	1.085	0.011		0.042	1.011
Medicaid Eligibles (10,000s)	0.047		0.188	1.048	-0.021		0.073	0.979	0.106		0.132	1.112
Medicaid Eligibles × Rural	0.757	***	0.232	2.132	-0.525	***	0.198	0.592	-0.205		0.208	0.815
Medicare Insured (10,000s)	0.184	*	0.099	1.202	-0.114		0.279	0.893	0.080		0.132	1.084
Medicare Eligibles × Rural	-0.482		0.325	0.618	-0.135		0.257	0.874	-1.322	***	0.336	0.267
Unemployed (100s)	-0.014	***	0.004	0.986	0.002	*	0.001	1.002	0.001		0.002	1.001
Pregnancies (100s)	0.221	***	0.053	1.247	-0.102	***	0.017	0.903	-0.074	**	0.036	0.928
Per-capita Income (10,000 $)	-0.793	***	0.230	0.453	0.168		0.113	1.183	-0.489	***	0.148	0.613
Industrial Establishments (100s)	0.017		0.018	1.017	0.028	***	0.005	1.028	0.010		0.010	1.010
Older Population (65+) (1,000s)	0.257	***	0.042	1.293	-0.105	***	0.028	0.901	-0.082	***	0.027	0.921
Local Education Expenditures (10 Million $)	-0.336	***	0.129	0.715	-0.047		0.043	0.954	0.201	**	0.080	1.223
Total Education Expenditures (10 Million $)	0.103	*	0.056	1.109	0.085	***	0.024	1.088	-0.010		0.044	0.990
Public School Personnel (100s)	0.048		0.062	1.049	0.013		0.018	1.014	0.030		0.040	1.031
Public School Personnel with MA (100s)	-0.219	***	0.071	0.804	-0.031		0.021	0.969	-0.031		0.048	0.969
Average SAT Math (100s)	-1.016		0.641	0.362	-3.324	***	0.493	0.036	-2.681	***	0.556	0.068
Average SAT Verbal (100s)	1.097		0.667	2.994	1.272	**	0.502	3.567	1.630	***	0.579	5.106
Primary Care Physicians	0.007	***	0.003	1.007	-0.001		0.001	0.999	-0.001		0.002	0.999
Medical Specialists	0.030	***	0.005	1.030	0.001		0.001	1.001	-0.007	***	0.002	0.993
Surgical Specialists	-0.016	**	0.006	0.984	-0.005	**	0.002	0.995	-0.004		0.004	0.996
Hospital Specialists	-0.006		0.005	0.994	0.002		0.002	1.002	0.010	***	0.003	1.010
Other Specialists	-0.057	***	0.007	0.945	0.014	***	0.002	1.014	0.004		0.004	1.004
Year	0.752	**	0.302	2.121	0.279		0.178	1.322	0.671	**	0.284	1.955
Year Squared	-2.235	***	0.632	0.107	-0.821	**	0.368	0.440	-1.681	***	0.586	0.186
Year Cubed	1.661	***	0.396	5.267	0.480	**	0.232	1.616	1.076	***	0.367	2.934
Constant	5.021		3.255		16.858	***	1.931		12.659	***	2.655	

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. All categories are relative to moving within the county to urban zipcode. Coefficients of permanent and time-varying heterogeneity are listed in Table A.12.

Table A.9: Estimation Results: Facility Outcome at End of Period

	Solo Practice				Hospital ER				Hospital Non-ER			
	Coeff	Signif	SD	Odds	Coeff	Signif	SD	Odds	Coeff	Signif	SD	Odds
Endogenous Var												
Moved in Previous Period	0.109		0.091	1.115	0.342	**	0.141	1.408	-0.006		0.074	0.994
Current Average Salary (10,000 $)	-0.012	***	0.002	0.988	-0.024	***	0.006	0.976	-0.002		0.002	0.998
Current Salary Rank	0		0.001	1	0.003		0.003	1.003	0.001		0.001	1.001
Current Hours of Direct Patient Care	-0.004	**	0.002	0.996	-0.016	***	0.003	0.984	-0.011	***	0.002	0.989
Current Rural Location	0.065		0.053	1.067	-0.136		0.115	0.873	-0.068		0.058	0.935
Facility (relative to Group Practice)												
Solo Practice	6.662	***	0.167	781.73	5.811	***	0.292	333.829	5.355	***	0.244	211.751
Hospital: ER Related	3.247	***	0.236	25.716	46.438	***	0.576	1.47E+20	37.554	***	1.13	2.04E+16
Hospital: Non ER related	3.071	***	0.171	21.57	39.726	***	0.838	1.79E+17	40.444	***	1.135	3.67E+17
Medical School/Parent University	-0.958	***	0.184	0.384	1.094	***	0.194	2.986	1.035	***	0.114	2.816
Other Facility	3.026	***	0.187	20.609	40.961	***	0.584	6.15E+17	37.331	***	1.138	1.63E+16
Specialty (relative to Generalist)												
Medical Specialist	-0.017		0.051	0.983	-0.678	***	0.149	0.508	-0.119	**	0.053	0.887
Surgical specialist	0.029		0.052	1.03	-1.192	***	0.155	0.304	-0.608	***	0.06	0.545
Hospital specialist	0.205	***	0.075	1.227	1.85	***	0.098	6.36	1.113	***	0.062	3.044
Other specialist	0.628	***	0.062	1.874	0.093		0.143	1.097	0.417	***	0.068	1.518
Individual Characteristics												1
Female	-0.032		0.041	0.969	-0.276	***	0.075	0.759	-0.175	***	0.04	0.84
Race (relative to Caucasian)												
African American	0.436	***	0.062	1.547	0.286	**	0.125	1.331	0.136	**	0.063	1.146
Asian	0.398	***	0.06	1.488	0.244	*	0.125	1.277	0.248	***	0.059	1.281
Hispanic	0.235	**	0.113	1.265	0.471	**	0.188	1.602	0.194	*	0.113	1.214
Other Race	0.282	***	0.075	1.326	0.164		0.13	1.178	0.107		0.071	1.113
Foreign Born	0.313	***	0.057	1.367	-0.073		0.115	0.929	0.185	***	0.056	1.203
Age	0.219	***	0.072	1.245	0.103		0.122	1.109	0.021		0.073	1.021
Age Squared (divided by 100)	-0.271	**	0.138	0.762	-0.132		0.243	0.876	0.051		0.147	1.052
Age Cubed (divided by 10,000)	0.118		0.085	1.126	0.059		0.156	1.061	-0.074		0.096	0.929
Experience	0.012		0.012	1.012	-0.007		0.022	0.993	-0.045	***	0.012	0.956
Experience Squared (divided by 100)	-0.114	**	0.056	0.892	-0.124		0.11	0.883	0.066		0.064	1.068
Experience Cubed (divided by 10,000)	0.171	**	0.074	1.186	0.232		0.152	1.262	-0.003		0.095	0.997
Exogenous Var												
Births (1000s)	-0.205		0.167	0.815	-0.506		0.348	0.603	-0.215		0.164	0.806
Gross Retail Sales (Billion $)	-0.029		0.034	0.971	-0.184	**	0.081	0.832	-0.125	***	0.034	0.883
Hospital Discharges (1000s)	-0.004		0.009	0.996	-0.03		0.02	0.971	-0.019	**	0.009	0.981
Acute Care/Hospital Beds (100s)	-0.038		0.028	0.963	-0.098	*	0.056	0.907	-0.039		0.027	0.962
Population (10,000s)	0.004		0.015	1.004	-0.023		0.033	0.977	-0.055	***	0.014	0.947
Midlevel Practitioners	0		0.001	1	-0.001		0.002	0.999	0.001		0.001	1.001
Registered Nurses (1000s)	-0.067		0.099	0.935	0.423	**	0.198	1.526	-0.019		0.097	0.981
Long-term Care/Nursing Home Beds (100s)	-0.006		0.02	0.994	0.031		0.04	1.031	0.103	***	0.02	1.108
Medicaid Eligibles (10,000s)	-0.044		0.056	0.957	0.173		0.117	1.188	0.004		0.055	1.004
Medicare Insured (10,000s)	-0.085		0.06	0.919	-0.136		0.107	0.873	-0.244	*	0.129	0.784
Unemployed (100s)	0.001		0.001	1.001	0.004	**	0.002	1.004	0.002	**	0.001	1.002
Pregnancies (100s)	0.023		0.014	1.023	0.059	**	0.03	1.061	0.038	***	0.014	1.039
Per-capita Income (10,000 $)	0.016		0.074	1.016	-0.237		0.156	0.789	-0.127	*	0.077	0.881
Industrial Establishments (100s)	-0.001		0.004	0.999	0.009		0.009	1.009	0.001		0.004	1.001
Older Population (65+) (1,000s)	0.023	*	0.013	1.023	0.017		0.024	1.017	0.013		0.016	1.013
Local Education Expenditures (10 Million $)	0.047		0.033	1.048	0.03		0.071	1.031	-0.009		0.033	0.991
Total Education Expenditures (10 Million $)	-0.02		0.018	0.98	-0.036		0.037	0.964	-0.005		0.018	0.995
Public School Personnel (100s)	-0.003		0.015	0.997	-0.02		0.032	0.981	0.016		0.015	1.016
Public School Personnel with MA (100s)	0.009		0.018	1.009	0.055		0.038	1.056	0.022		0.017	1.023
Average SAT Math (100s)	0.401		0.282	1.494	-0.419		0.639	0.658	-0.174		0.304	0.84
Average SAT Verbal (100s)	-0.473		0.293	0.623	0.337		0.665	1.4	0.283		0.317	1.328
Primary Care Physicians	0.001		0.001	1.001	0.002		0.002	1.002	-0.001		0.001	0.999
Medical Specialists	0		0.001	1	0.002		0.002	1.002	-0.003	***	0.001	0.997
Surgical Specialists	-0.002		0.002	0.998	-0.014	***	0.004	0.986	-0.003		0.002	0.997
Hospital Specialists	0.001		0.001	1.001	0.004		0.003	1.004	0.005	***	0.001	1.005
Other Specialists	0.001		0.002	1.001	0.005		0.004	1.005	0.007	***	0.002	1.007
Year	-0.431	***	0.119	0.65	-0.887	***	0.231	0.412	-1.033	***	0.115	0.356
Year Squared	0.643	**	0.262	1.902	1.943	***	0.511	6.982	2.292	***	0.254	9.899
Year Cubed	-0.329	*	0.171	0.72	-1.18	***	0.339	0.307	-1.412	***	0.167	0.244
Constant	-4.482	***	1.35	0.011	-1.688		2.319	0.185	0.368		1.333	1.444

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. Coefficients of permanent and time-varying heterogeneity are listed in Table A.12. The results are all relative to the omitted facility category of group practice.

Table A.10: Estimation Results: Facility Outcome at End of Period Continued

	Medical School Related				Other Facility			
	Coeff	Signif	SD	Odds	Coeff	Signif	SD	Odds
Endogenous Var								
Moved in Previous Period	0.09		0.163	1.094	0.09		0.111	1.094
Current Average Salary (10,000 $)	-0.006		0.004	0.994	-0.026	***	0.004	0.974
Current Salary Rank	-0.008	**	0.004	0.992	0.001		0.002	1.001
Current Hours of Direct Patient Care	0.01	***	0.003	1.01	-0.031	***	0.003	0.969
Current Rural Location	0.057		0.142	1.059	-0.13		0.087	0.878
Facility (relative to Group Practice)								
Solo Practice	1.139	***	0.2	3.125	5.253	***	0.255	191.08
Hospital: ER Related	3.622	***	0.208	37.412	42.982	***	0.464	4.64E+18
Hospital: Non ER related	3.941	***	0.088	51.489	39.644	***	1.108	1.65E+17
Medical School/Parent University	8.154	***	0.167	3478.652	-0.415	**	0.169	0.66
Other Facility	2.134	***	0.174	8.453	47.741	***	3.509	5.42E+20
Specialty (relative to Generalist)								
Medical Specialist	0.459	***	0.092	1.582	-0.785	***	0.094	0.456
Surgical specialist	0.442	***	0.11	1.556	-0.693	***	0.101	0.5
Hospital specialist	1.045	***	0.111	2.843	0.751	***	0.104	2.118
Other specialist	0.228	*	0.138	1.257	0.555	***	0.084	1.741
Individual Characteristics								
Female	-0.027		0.073	0.974	0.317	***	0.065	1.374
Race (relative to Caucasian)								
African American	-0.226	*	0.137	0.797	0.415	***	0.093	1.514
Asian	0.222	**	0.108	1.248	0.199	**	0.094	1.221
Hispanic	0.465	**	0.188	1.591	0.479	***	0.183	1.614
Other Race	-0.036		0.145	0.965	0.193	*	0.115	1.212
Foreign Born	0.162		0.103	1.176	-0.066		0.088	0.936
Age	-0.061		0.143	0.941	-0.017		0.104	0.983
Age Squared (divided by 100)	0.236		0.289	1.266	0.195		0.2	1.215
Age Cubed (divided by 10,000)	-0.182		0.189	0.833	-0.162		0.125	0.851
Experience	-0.048	**	0.022	0.953	-0.047	**	0.018	0.955
Experience Squared (divided by 100)	-0.064		0.117	0.938	0.122		0.086	1.13
Experience Cubed (divided by 10,000)	0.21		0.171	1.234	-0.107		0.114	0.899
Exogenous Var								
Births (1000s)	-1.647	***	0.37	0.193	-0.443	*	0.254	0.642
Gross Retail Sales (Billion $)	-0.051		0.094	0.95	-0.105	**	0.052	0.9
Hospital Discharges (1000s)	0.105	***	0.03	1.11	-0.01		0.014	0.99
Acute Care/Hospital Beds (100s)	0.207	**	0.082	1.23	-0.072		0.044	0.93
Population (10,000s)	0.011		0.056	1.011	-0.019		0.023	0.981
Midlevel Practitioners	-0.005	***	0.002	0.995	0		0.001	1
Registered Nurses (1000s)	1.24	***	0.277	3.455	0.132		0.166	1.141
Long-term Care/Nursing Home Beds (100s)	-0.179	***	0.058	0.836	0.039		0.032	1.04
Medicaid Eligibles (10,000s)	-0.193		0.136	0.825	-0.095		0.086	0.909
Medicare Insured (10,000s)	0.323	**	0.159	1.381	0.023		0.157	1.023
Unemployed (100s)	0		0.002	1	0.002		0.001	1.002
Pregnancies (100s)	0.096	***	0.032	1.1	0.068	***	0.021	1.07
Per-capita Income (10,000 $)	0.246		0.199	1.279	-0.292	**	0.116	0.747
Industrial Establishments (100s)	-0.023	**	0.012	0.977	-0.008		0.006	0.992
Older Population (65+) (1,000s)	-0.124	***	0.035	0.883	0.012		0.022	1.012
Local Education Expenditures (10 Million $)	-0.029		0.093	0.971	0.08		0.052	1.084
Total Education Expenditures (10 Million $)	0.075		0.047	1.078	-0.024		0.027	0.976
Public School Personnel (100s)	-0.024		0.035	0.977	-0.015		0.023	0.985
Public School Personnel with MA (100s)	-0.017		0.044	0.983	0.009		0.028	1.009
Average SAT Math (100s)	-1.484	**	0.726	0.227	-0.245		0.429	0.783
Average SAT Verbal (100s)	0.971		0.709	2.64	0.443		0.45	1.557
Primary Care Physicians	0.002		0.001	1.002	-0.002		0.001	0.998
Medical Specialists	0.003	**	0.002	1.003	-0.003	**	0.002	0.997
Surgical Specialists	-0.004		0.004	0.996	0.001		0.003	1.001
Hospital Specialists	-0.003		0.003	0.997	0.004	**	0.002	1.004
Other Specialists	0.006		0.004	1.006	0.003		0.003	1.003
Year	1.447	***	0.251	4.249	-0.313	*	0.175	0.731
Year Squared	-3.001	***	0.597	0.05	0.669	*	0.383	1.951
Year Cubed	1.662	***	0.417	5.267	-0.396		0.251	0.673
Constant	-40.37	***	1.389	0	-0.016		2.006	0.984

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. Coefficients of permanent and time-varying heterogeneity are listed in Table A.12. The results are all relative to the omitted facility category of group practice.

Table A.11: Estimation Results: Hours of Direct Patient Care at Beginning of Period

	Coeff	Signif	SD	Odds
Current Average Salary (10,000 $)	0.018	***	0.006	1.018
Average Salary × Rural	0.017	*	0.010	1.017
Current Salary Rank	0.003		0.003	1.003
Previous Hours Worked	0.334	***	0.005	1.396
Experience	-0.279	***	0.050	0.756
Experience Squared (divided by 100)	1.344	***	0.300	3.834
Experience Cubed (divided by 10,000)	-1.582	***	0.495	0.205
Current Rural Location	0.689	***	0.201	1.991
Moved in Previous Period	-0.615		0.428	0.541
Facility (relative to Group Practice)				
Solo Practice	0.618	**	0.285	1.855
Hospital: ER Related	-0.578		0.372	0.561
Hospital: Non ER related	0.794	***	0.290	2.211
Medical School/Parent University	0.785	*	0.402	2.192
Other Facility	-4.207	***	0.466	0.015
Specialty (relative to Generalist)				
Medical Specialist	0.471	**	0.224	1.602
Surgical specialist	0.601	*	0.309	1.824
Hospital specialist	-3.548	***	0.334	0.029
Other specialist	-0.991	***	0.285	0.371
Individual Characteristics				
Female	-3.506	***	0.151	0.030
Race (relative to Caucasian)				1.000
African American	1.782	***	0.223	5.939
Asian	-0.027		0.210	0.973
Hispanic	1.107	***	0.373	3.025
Other Race	0.308		0.240	1.360
Foreign Born	1.163	***	0.211	3.200
Age	-0.490		0.514	0.613
Age Squared (divided by 100)	1.630		1.053	5.106
Age Cubed (divided by 10,000)	-1.741	**	0.698	0.175
County Characteristics				1.000
Births (1000s)	-1.330	***	0.416	0.264
Gross Retail Sales (Billion $)	-0.275	***	0.072	0.760
Retail Sale × Rural	-1.329	***	0.499	0.265
Hospital Discharges (1000s)	0.052	**	0.021	1.053
Acute Care/Hospital Beds (100s)	-0.146	*	0.078	0.864
Population (10,000s)	0.106	***	0.031	1.112
Population × Rural	0.355	***	0.113	1.426
Midlevel Practitioners	-0.015	***	0.002	0.986
Midlevel Practitioner × Rural	0.009		0.009	1.009
Registered Nurses (1000s)	-0.632	**	0.289	0.531
Registered Nurses × Rural	-0.395		0.855	0.674
Long-term Care/Nursing Home Beds (100s)	-0.011		0.053	0.989
Medicaid Eligibles (10,000s)	-0.419	***	0.126	0.658
Medicaid Eligibles × Rural	-0.680	**	0.277	0.507
Medicare Insured (10,000s)	0.812	***	0.212	2.253
Medicare Eligibles × Rural	-0.747		0.536	0.474
Unemployed (100s)	-0.016	***	0.002	0.984
Pregnancies (100s)	0.116	***	0.034	1.123
Per-capita Income (10,000 $)	-0.636	***	0.205	0.530
Industrial Establishments (100s)	-0.008		0.011	0.992
Older Population (65+) (1,000s)	0.042		0.038	1.043
Local Education Expenditures (10 Million $)	-0.309	***	0.075	0.734
Total Education Expenditures (10 Million $)	0.167	***	0.041	1.182
Public School Personnel (100s)	-0.117	***	0.032	0.890
Public School Personnel with MA (100s)	0.045		0.039	1.046
Average SAT Math (100s)	2.532	***	0.778	12.583
Average SAT Verbal (100s)	-4.712	***	0.803	0.009
Primary Care Physicians	0.000		0.002	1.000
Medical Specialists	0.002		0.002	1.002
Surgical Specialists	0.020	***	0.004	1.020
Hospital Specialists	0.013	***	0.003	1.013
Other Specialists	-0.012	***	0.005	0.988
Year	-8.578	***	0.408	
Year Squared	14.018	***	0.724	
Year Cubed	-6.875	***	0.391	
Constant	49.396	***	8.189	

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. Coefficients of permanent and time-varying heterogeneity are listed in Table A.12.

Table A.12: Estimation Results: UH Coefficients

	Estimated Permanent Mass Points						Estimated Time Varying Mass Points	
	2		3		4		2	
	Coeff	Std. Error	Coeff	Std. Error	Coeff	Std. Error	Coeff	Std. Error
Activity and Movement								
Move within NC	0.565	0.160	0.600	0.157	0.464	0.161	-1.314	0.038
Move out of NC	0.550	0.229	0.542	0.204	1.323	0.223	45.418	0.654
Inactive	1.490	0.287	0.175	0.283	0.444	0.305	-2.476	0.367
Rurality and Movement								
Move within the County to Rural Zip.	0.456	0.399	0.398	0.382	-0.051	0.395	-0.204	0.129
Move out of the County to Urban Zip.	0.138	0.248	0.529	0.229	0.048	0.242	-0.723	0.067
Move out of the County to Rural Zip.	-0.246	0.366	0.374	0.328	0.099	0.352	-0.856	0.120
Facility								
Solo Practice	-7.942	0.346	-8.210	0.345	-7.945	0.375	-4.290	0.690
Hospital ER	-8.083	0.438	8.862	0.415	9.796	0.466	26.531	1.396
Hospital Non-ER	-30.969	0.345	-31.590	0.338	-30.770	0.358	-37.626	0.043
Medical School Related	6.570	0.398	8.289	0.385	7.714	0.419	5.219	1.196
Other facility	-28.061	0.433	-28.610	0.435	-28.306	0.489	-3.380	0.555
Hours of Direct Patient Care	-11.00	0.699	2.116	0.698	12.997	0.751	-1.919	0.199
Estimated Probability Weight	0.137		0.612		0.212		0.899	

A.5 Results from Policy Experiment Comparing Between Zipcode and County Level Shocks

Table A.13: Wage Experiments

	All		Male		Female	
	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year
Benchmark	8.21	15.55	10.85	20.73	7.27	13.68
Increase salary of all rural county by $200,000 in all years	7.95	15.15	6.93	13.10	10.75	20.76
Increase salary of all rural zipcode by $200,000 in all years	7.97	15.16	10.74	20.58	6.96	13.18
Increase salary of all rural county by 5% in all years	7.25	14.51	6.38	12.58	10.38	19.96
Increase salary of all rural zipcode by 5% in all years	7.29	14.39	9.79	19.48	6.34	12.44

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table A.14: Midlevel Practitioners and RN Experiments

	All		Male		Female	
	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year
Benchmark	8.21	15.55	10.85	20.73	7.27	13.68
Increase midlevel practitioner in rural county by 5% in all years	9.50	16.84	8.38	14.67	12.51	22.59
Increase midlevel practitioner in rural zipcode by 5% in all years	10.54	18.46	13.68	23.94	9.33	16.33
increase RN in rural county by 5% in all years	7.08	15.13	6.16	13.16	10.49	20.33
increase RN in rural zipcode by 5% in all years	7.59	14.89	10.24	20.25	6.57	12.81

Table A.15: Midlevel Practitioners and RN Experiments

	All		Male		Female	
	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year	Prob of Moving after 1 year	Prob of Moving after 2 year
Benchmark	8.21	15.55	10.85	20.73	7.27	13.68
Increase Medicaid in rural county by 10% in all years	10.03	17.10	8.82	14.96	13.30	22.81
Increase Medicaid in rural zipcode by 10% in all years	11.71	19.52	14.91	25.23	10.46	17.26
Increase Medicare in rural county by 10% in all years	9.98	17.24	8.78	15.07	13.09	22.82
Increase Medicare in rural zipcode by 10% in all years	11.79	19.70	14.84	25.05	10.59	17.57

Note: Percentage change in probability is calculated as the relative change between the simulated data without the policy and the simulated data with the policy.

Table A.16: Comparing Physician Characteristics Across Policy Simulations in All Counties

Stay in the Same Zipcode

Variable	Benchmark	100K Salary Increase	5% Salary Increase	5% RN Increase	5% Midlevel Increase	Medicaid with Salary Increase
Female(%)	24.70	24.71	24.68	25.28	24.99	24.70
Age	50.00	50.01	50.03	49.47	49.77	50.01
Experience	16.50	16.50	16.53	16.05	16.11	16.45
Caucasian (%)	74.39	74.39	74.48	74.4	74.38	74.43
African American(%)	7.58	7.56	7.56	7.58	7.62	7.59
Asian(%)	9.84	9.81	9.75	9.81	9.82	9.77
Hispanic(%)	2.33	2.35	2.34	2.34	2.33	2.35
Other Race(%)	5.85	5.88	5.86	5.87	5.84	5.87
Foreign Born(%)	8.83	8.84	8.83	8.94	8.88	8.86
Generalist (%)	36.47	36.44	36.58	35.31	35.81	35.97
Medical Specialist(%)	16.75	16.85	16.71	17.72	17.09	16.92
Surgical specialist(%)	21.66	21.69	21.61	21.64	21.86	21.94
Hospital specialist(%)	18.24	18.18	18.36	18.33	18.30	18.37
Other specialist(%)	6.89	6.84	6.73	7.01	6.94	6.80

Move within NC

	Benchmark	100K Salary Increase	5% Salary Increase	5% RN Increase	5% Midlevel Increase	Medicaid with Salary Increase
Female(%)	27.58	27.55	28.03	24.53	28.27	28.48
Age	48.62	48.59	48.31	50.75	47.99	47.91
Experience	15.23	15.21	14.97	17.09	14.68	14.63
Caucasian (%)	65.63	65.76	65.65	65.68	65.7	65.51
African American(%)	10.75	10.78	10.87	10.6	10.44	10.86
Asian(%)	12.02	12.17	12.20	12.37	12.18	12.32
Hispanic(%)	3.31	3.23	3.14	3.28	3.41	3.25
Other Race(%)	8.29	8.07	8.14	8.07	8.28	8.07
Foreign Born(%)	10.09	10.08	10.19	9.16	10.22	10.34
Generalist (%)	37.37	37.44	37.21	40.17	35.90	36.12
Medical Specialist(%)	13.76	13.86	14.20	13.38	14.57	14.61
Surgical specialist(%)	16.14	16.07	16.16	18.57	16.53	16.38
Hospital specialist(%)	23.84	23.88	23.6	20.87	24.07	23.90
Other specialist(%)	8.89	8.74	8.83	7.00	8.93	8.99

Note: Aside from age and experience, all variables are reported in percentage.

Table A.17: Comparing Physician Characteristics Across Policy Simulations in Rural Counties

Stay in the Same Zipcode						
Variable	Benchmark	100K Salary Increase	5% Salary Increase	5% RN Increase	5% Midlevel Increase	Medicaid with Salary Increase
Female(%)	22.21	22.33	22.38	23.42	22.53	21.88
Age	51.73	51.69	51.67	50.82	51.71	52.14
Experience	17.73	17.68	17.63	16.81	16.87	17.89
Caucasian (%)	73.51	73	73.52	72.95	73.32	73.28
African American(%)	7.83	8.02	7.96	8.09	7.92	8
Asian(%)	9.36	9.67	9.33	9.44	9.52	9.39
Hispanic(%)	2.40	2.62	2.52	2.57	2.48	2.59
Other Race(%)	6.91	6.69	6.67	6.95	6.76	6.74
Foreign Born(%)	9.25	9.47	9.32	9.92	9.43	9.17
Generalist (%)	44.36	44.11	44.08	43.07	44.67	43.2
Medical Specialist(%)	11.95	12.05	11.86	12.63	11.68	11.53
Surgical specialist(%)	20.12	20.23	20.51	19.4	19.23	20.71
Hospital specialist(%)	18.05	18.11	18.39	18.91	18.64	18.98
Other specialist(%)	5.52	5.49	5.15	5.98	5.78	5.57

Move within NC						
	Benchmark	100K Salary Increase	5% Salary Increase	5% RN Increase	5% Midlevel Increase	Medicaid with Salary Increase
Female(%)	24.64	24.63	25.24	21.34	25.74	26.38
Age	50.55	50.51	50.01	51.77	49.66	49.32
Experience	16.64	16.6	16.09	17.77	15.64	15.42
Caucasian (%)	63.5	63.48	64.52	64.75	63.92	63.61
African American(%)	11.72	10.92	11.42	10.93	10.62	11.66
Asian(%)	11.38	11.63	11.11	11.65	11.76	11.57
Hispanic(%)	3.61	4.12	3.48	3.51	3.76	3.48
Other Race(%)	9.79	9.86	9.47	9.16	9.94	9.68
Foreign Born(%)	10.59	10.60	10.84	9.73	11.36	11.24
Generalist (%)	44.62	44.4	45.79	43.27	43.54	43.81
Medical Specialist(%)	9.73	10.19	10.11	12.11	10.68	10.30
Surgical specialist(%)	14.99	14.97	14.74	19.07	14.27	14.13
Hospital specialist(%)	23.64	23.52	22.41	19.61	24.2	24.37
Other specialist(%)	7.02	6.93	6.95	5.93	7.32	7.39

Note: Aside from age and experience, all variables are reported in percentage.

APPENDIX B

APPENDIX FOR CHAPTER 3: IDENTIFYING THE EFFECT OF PHYSICIAN SUPPLY ON AMBULATORY CARE SENSITIVE CONDITION ADMISSIONS

B.1 Tables and Figures

Table B.1: ICD-9 Codes for Ailments

Ailment	ICD-9 Code	Subcategory
COPD	490,491,492,492,494	Chronic
asthma	493	Chronic
diabetes	250	Chronic
epilepsy	345	Chronic
congestive heart failures	428	Chronic
hypertension	401.9	Chronic
pneumonia	495,486	Acute
tuberculosis	011	Acute
UTI	599	Acute
hypoglycemia	251.2	Acute
cellulitis	682.9	Acute
hypokalemia	276.8	Acute
ulcer	531,532	Acute
severe ENT Infection	381,461,462	Acute
Gangrene	785.4	Preventable
Influenza	487	Preventable
Malnutrition	262,263	Preventable

Table B.2: Compare Urban and Rural Ratio of ACSC Occurrences

	Chronic		Acute		Preventable		ACSC	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
2003	0.4485	0.5173	0.1491	0.1709	0.0164	0.0183	0.5014	0.5766
SE	0.0006	0.0008	0.0004	0.0006	0.0002	0.0002	0.0006	0.0008
2004	0.4555	0.5346	0.1563	0.1811	0.0200	0.0221	0.5110	0.5958
SE	0.0006	0.0008	0.0004	0.0006	0.0002	0.0002	0.0006	0.0008
2005	0.4635	0.5422	0.1626	0.1836	0.0190	0.0207	0.5179	0.6005
SE	0.0006	0.0008	0.0004	0.0006	0.0002	0.0002	0.0006	0.0008
2006	0.4630	0.5350	0.2032	0.2310	0.0183	0.0203	0.5352	0.6132
SE	0.0006	0.0008	0.0005	0.0007	0.0002	0.0002	0.0006	0.0008
2007	0.4648	0.5395	0.2100	0.2352	0.0184	0.0223	0.5396	0.6173
SE	0.0006	0.0008	0.0005	0.0007	0.0002	0.0002	0.0006	0.0008

All values are significantly different from each other by T-test with p-value < 0.01.

Table B.3: Breakdown of Percentage of ACSC Related Ailments-By Year

	2003	2004	2005	2006	2007
Chronic					
COPD	11.44	11.74	12.15	12.15	12.01
Asthma	4.82	5.01	5.17	5.17	5.21
diabetes	16.95	17.35	17.56	17.56	17.72
epilepsy	0.29	0.26	0.28	0.28	1.14
congestive heart failure	10.65	10.99	11.14	11.14	10.7
hypertension	28.14	29.08	29.66	29.66	28.08
Acute					
Pneumonia	5.25	5.39	5.5	5.5	5.55
TB	0.04	0.03	0.03	0.03	0.03
UTI	6.93	7.44	7.74	7.74	8.28
hypoglycemia	0.1	0.1	0.1	0.1	0.12
cellulitis	0.04	0.05	0.05	0.05	0.06
hypokalemia	3.85	4.23	4.45	4.45	4.57
ulcer	0.79	0.8	0.76	0.76	0.7
severe ENT infection	0.36	0.33	0.33	0.33	0.3
Preventable					
gangrene	0.27	0.28	0.27	0.27	0.24
influenza	0.05	0.35	0.2	0.2	0.11
malnutrition	1.42	1.48	1.51	1.51	1.64

Percentage recorded is the ratio between number of ACSC diagnosis and the total number of admitted occurrences in the data.

Table B.4: Breakdown of ACSC Related Groups-By year

	ACSC		Non-ACSC		Chronic		Non-Chronic		Acute		Non-Acute	
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.
2003	562449	52.95	499719	47.05	503490	47.4	558678	52.6	166401	15.67	895767	84.33
2004	588956	54.25	496773	45.75	526276	48.47	559453	51.53	179182	16.5	906547	83.5
2005	602299	54.86	495622	45.14	540752	49.25	557169	50.75	186541	16.99	911380	83.01
2006	625584	56.34	484763	43.66	542980	48.9	567367	51.1	236045	21.26	874302	78.74
2007	638832	56.78	486261	43.22	553195	49.17	571898	50.83	245839	21.85	879254	78.15
	Preventable		Non-Preventable		Multiple Categories		Single Categories					
	Count	Perc.	Count	Perc.	Count	Perc.	Count	Perc.				
2003	18174	1.71	1043994	98.29	121744	11.46	940424	88.54				
2004	22657	2.09	1063072	97.91	134420	12.38	951309	87.62				
2004	21464	1.95	1076457	98.05	141558	12.89	956363	87.11				
2006	21026	1.89	1089321	98.11	168381	15.16	941966	84.84				
2007	22198	1.97	1102895	98.03	175877	15.63	949216	84.37				

Note: 1) All values are significantly different from each other by T-test with p-value < 0.01.

2) Percentage reported is the ratio between number of ASCS in the group and total admission into the hospital.

Table B.5: Cost Comparison of ACSC related Ailment Groups

	ACSC	Non-ACSC	Chronic	Non-Chronic	Acute	Non-Acute	Preventable	Non-Preventable	Multiple Group	Single Occurance
2003	16686.19	9821.506	16274.76	10911.92	18173.59	12585.26	32985.98	13116.59	18939.96	12746.69
2004	18324.39	10790.47	17906.85	12022.09	19826.53	13904.32	31243.26	14528.46	20338.54	14105.59
2005	19708.11	11527.43	19286.71	12834.14	20869.55	15026.89	36097.11	15614.78	21544.53	15196.76
2006	21055.73	12423.22	20796.92	13920.24	21069.11	16270.51	39144.39	16865	23117.09	16431.23
2007	22477.42	13243.22	22141.55	14943.35	22340.38	17413.15	41824.11	18016.72	24456.89	17590.98

All values are significantly different from each other by T-test with p-value < 0.01.

Table B.6: Cost Comparison of ACSC related Ailment Groups-By Year

	2003	2004	2005	2006	2007
Chronic					
COPD	17699.28	19220.6	20809.9	22277.11	23664.31
	12908.41	14299.77	15352.12	16614.69	17779.7
Asthma	12517.99	14108.15	15145.56	16514.95	18045.53
	13504.05	14917.85	16062.65	17329.68	18510.69
diabetes	15645.98	17086.62	18306.75	19640.66	20933.54
	13009.57	14413.38	15526.94	16785.26	17959.27
epilepsy	18618.88	19035.5	20783.76	23073.99	19649.29
	13441.76	14866.27	16001.73	17270.08	18473.07
congestive heart failure	20392.26	22321.84	24169.95	25843.68	27120.58
	12629.61	13957.81	14992.61	16239.46	17452.32
hypertension	15137.63	16641.14	17891.58	19329.09	20524.17
	12798.17	14154.09	15223.91	16457.49	17690.99
Acute					
Pneumonia	20149.83	22230.98	23349.99	25211.73	27230.24
	13085.65	14458.63	15588.16	16831.49	17972.8
TB	21436.82	27721.97	23118.23	23793.63	27707.28
	13453.62	14873	16012.98	17284.74	18483.61
UTI	19359.64	21241.69	22394.14	24265.36	25443.79
	13017.18	14365.68	15479.91	16681	17858.48
hypoglycemia	10440.65	12599.8	14888.65	15151.56	16304.38
	13459.6	14879.58	16016.36	17289.34	18489.05
cellulitis	19461.42	23224.65	21803.64	26163.12	26881.4
	13454.27	14873.44	16012.3	17282.01	18481.42
hypokalemia	14440.35	15491.79	16293.76	17198.65	18438.16
	13417.14	14850.13	16002.22	17198.65	18488.74
ulcer	21092.07	21565.54	22712.28	23771.67	26163.5
	13395.89	14823.36	15964.07	17239.21	18432.06
severe ENT infection	11304.07	11739.53	13283.68	13168.21	14148.34
	13464.27	14887.64	16024.25	17299.98	18499.63
Preventable					
gangrene	28889.64	32824.3	32979.94	36274.37	38886.79
	13414.87	14827.06	15969.04	17236.96	18436.58
influenza	11586.65	10599.37	12656.83	12700.83	13721.51
	13457.41	14892.4	16021.8	17293.71	18491.61
malnurtrition	34623.63	36180.78	39931.73	42519.73	44267.34
	13152.59	14557.62	15648.33	16903.06	18057.25

1) All values are significantly different from each other by T-test with p-value < 0.01, except: 2005 hypoglycemia, and 2006-2007 hypokalemia.

2) The unit is in American dollars, unadjusted for inflation.

Table B.7: Days Spent in Hospital Between ACSC Groups

	ACSC	Non-ACSC	Chronic	Non-Chronic	Acute	Non-Acute	Preventable	Non-Preventable	Multiple Group	Single Occurance
2003	5.599167	3.770023	5.374571	4.165467	6.993167	4.319793	12.07049	4.610974	7.320229	4.404401
2004	5.572837	3.794888	5.351183	4.202596	6.969316	4.322532	10.86724	4.629164	7.236624	4.4093
2005	5.539003	3.807022	5.314939	4.215805	6.867257	4.325259	11.61377	4.620437	7.12657	4.406441
2006	5.47654	3.802978	5.237554	4.224148	6.768758	4.293979	11.61976	4.586538	6.994237	4.385909
2007	5.44715	3.833426	5.192786	4.270915	6.724831	4.298615	11.70948	4.583595	6.931318	4.393161

All values are significantly different from each other by T-test with p-value < 0.01.

Table B.8: Days Spent in Hospital Between ACSC Groups-By Year

	2003	2004	2005	2006	2007
Chronic					
COPD	6.22	6.19	6.18	6.07	5.99
	4.55	4.57	4.56	4.54	4.55
Asthma	4.41	4.49	4.47	4.74	4.74
	4.76	4.77	4.77	4.38	4.46
diabetes	5.35	5.28	5.21	5.10	5.04
	4.61	4.65	4.66	4.64	4.66
epilepsy	5.81	5.56	5.55	5.78	5.25
	4.74	4.76	4.75	4.72	4.72
congestive heart failure	6.77	6.72	6.69	6.54	6.50
	4.50	4.52	4.52	4.50	4.51
hypertension	4.81	4.76	4.69	4.62	4.52
	4.71	4.76	4.79	4.76	4.80
Acute					
Pneumonia	7.42	7.49	7.38	7.28	7.29
	4.59	4.60	4.60	4.57	4.57
TB	10.96	11.96	9.66	9.01	10.07
	4.74	4.76	4.76	4.72	4.72
UTI	7.89	7.89	7.77	7.70	7.55
	4.50	4.51	4.50	4.46	4.47
hypoglycemia	4.26	4.80	4.79	4.59	4.73
	4.74	4.76	4.76	4.72	4.72
cellulitis	7.89	8.86	8.39	8.29	8.28
	4.74	4.76	4.76	4.72	4.72
hypokalemia	5.59	5.49	5.38	5.21	5.18
	4.70	4.73	4.73	4.70	4.70
ulcer	6.69	6.40	6.29	6.14	6.31
	4.72	4.75	4.75	4.71	4.71
severe ENT infection	4.74	4.48	4.61	4.33	4.31
	5.01	4.76	4.76	4.72	4.73
Preventable					
gangrene	10.91	11.21	10.99	10.72	10.81
	4.72	4.74	4.74	4.70	4.71
influenza	4.37	4.43	4.82	4.41	4.52
	4.74	4.76	4.76	4.72	4.72
malnurtrition	12.63	12.44	12.71	12.56	12.37
	4.63	4.64	4.64	4.60	4.60

1) All values are significantly different from each other by T-test with p-value < 0.01, except: 2004-2007 hypoglycemia, 2005 ENT, and 2003, 200-2007 influenza

Table B.9: ACSC Admission Counts by Race and Gender

	Male	Female
Caucasian	938,392	1,289,655
Africian American	269,819	411,077
Asian & Native American	27,431	46,634
Others	68,064	123,600
Missing	917,786	1,388,517
Total	2,221,492	3,259,483

Table B.10: Summary Statistics: Distribution of PCPs overtime

All Counties				
Year	Mean	Std. Dev.	Min	Max
2003	72.65	127.77	1	724
2004	74.01	130.49	1	755
2005	76.60	136.91	1	798
2006	79.84	145.72	0	866
2007	80.93	150.29	0	917
Total	75.88	135.64	0	917

	Urban Counties		Rural Counties	
	Mean	Std. Dev.	Mean	Std. Dev.
2003	155.20	188.98	28.20	23.35
2004	158.26	193.07	28.65	23.76
2005	164.60	202.82	29.22	25.00
2006	173.63	216.02	29.34	25.56
2007	176.40	223.61	29.52	26.62
Total	165.62	203.12	28.98	24.73

Table B.11: County-Level Characteristics Over Time

	2002		2003		2004	
	Mean	Std.	Mean	Std.	Mean	Std.
Acute Care/Hospital Beds	209.3	331.6726	205.58	322.8209	205.9	323.3702
Long-term Care/Nursing Home Beds	430.82	485.4096	435.12	489.852	437.76	494.4008
Medicare Insured	9645.34	10456.3	9543.82	10312.49	9218.33	9810.277
Medicaid Eligibles	13900.28	14867.86	14472.83	15810.28	15123.6	16887.73
Per Capita Income	24908.76	3972.207	25391.19	3866.148	26908.7	4050.725
Population	83217.26	113962.2	84151.05	116357	85379.02	119095.3

	2005		2006		2007	
	Mean	Std.	Mean	Std.	Mean	Std.
Acute Care/Hospital Beds	203.38	323.6265	203.29	323.5224	203.22	325.9257
Long-term Care/Nursing Home Beds	439.87	496.0169	442.48	501.7826	442.1	500.1409
Medicare Insured	9736.58	10437.41	10102.38	10898.74	10353.02	11275.16
Medicaid Eligibles	15637.51	17859.86	16444.57	19068.42	16820.28	19671.09
Per Capita Income	28262.77	4186.869	29359.51	4544.235	30825.97	4762.536
Population	80466.68	108082.4	88836.95	127656.8	90827.23	132444.2

Table B.12: Comparing Univariate, Multivariate, and RD Regression Results

	Dep Variable: Number of ACSC Admissions		
	Coefficient	Std. Error	P-value
Univariate OLS	39.51	***	0.96
Multivariate OLS	-0.52		1.81
RD	-148.32	***	67.25

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. Multivariate regression included all independent variables used in stage 2 of IV regress.

Table B.13: RDD Result

Independent Variable	Estimate	Signf	Robust Std. Error
Number of Prime Care Physician	-148.323	***	67.253
Third Stage (Dep: ACSC Admission)			
Number of Short Term Care Beds	3.870	***	0.674
Number of Long Term Care Beds	-2.252	***	0.537
Number of Medicare Eligibles	0.352	***	0.028
Number of Medicaid	0.199	***	0.022
Per Capita Income	-0.016		0.011
Number of people under poverty line	-0.030		0.032
Metropolitan	43.006		106.556
Population	0.048	***	0.022
Second Stage (Dep: Prime Care Physicians)			
Pred. HPSA	4.409	***	2.225
Number of Short Term Care Beds	0.010	***	0.004
Number of Long Term Care Beds	-0.002		0.004
Number of Medicare Eligibles	0.001		0.000
Number of Medicaid	0.002	*	0.000
Per Capita Income	0.0001		0.000
Number of people under poverty line	-0.001	***	0.000
Metropolitan	-1.117		0.931
Population	0.0003	***	0.000
First Stage (Dep: HPSA Designation)			
Shortage Indicator	0.603	***	0.091
Number of Short Term Care Beds	-0.001	***	0.000
Number of Long Term Care Beds	0.001	***	0.000
Number of Medicare Eligibles	0.0000	***	0.000
Number of Medicaid	0.0000		0.000
Per Capita Income	0.0000	***	0.000
Number of people under poverty line	0.0000		0.000
Metropolitan	-1.6457		0.7890
Population	0.0000		0.000
N	500		
Adjusted R^2	0.982		

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$.

Table B.14: RD Model with Subcategories of ACSC Admission at Level

	DepVar: Number of Chronic ACSC		DepVar: Number of Acute ACSC		DepVar: Number of Preventable ACSC		DepVar: Number of Multiple ACSC	
Independent Variable	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error	Coefficient	Std. Error
Number of Primary Care Physicians	-55.065	7.233	-32.854	6.145	3.962	7.950	-24.433	26.847
Other Variables (Second Stage)								
Number of Short Term Care Beds	3.743	0.981	0.833	0.502	0.174	0.119	0.799	0.397
Number of Long Term Care Beds	2.547	0.660	1.070	0.355	0.108	0.070	-0.778	0.252
Number of Medicare Eligibles	0.339	0.037	0.123	0.018	0.004	0.004	0.095	0.014
Per Capita Income	0.033	0.012	-0.003	0.005	-0.001	0.001	-0.003	0.004
Unemployment	0.021	0.037	0.012	0.018	0.007	0.004	0.005	0.014
Population	0.018	0.024	0.001	0.011	-0.002	0.003	0.007	0.009
N	500.000		500.000		500.000		500.000	
R^2	0.981		0.970		0.916		0.964	

Note: *** means p-value is less than 0.01, ** means $p \leq 0.05$ and ** means $p \leq 0.1$. First stage also included exogenous independent variables from stage 2.

Table B.15: RD Model by Age and Gender

	ACSC Count			Chronic ACSC Count			Acute ACSC Count			Preventable ACSC Count		
	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value	Estimate	Std. Error	P-Value
Age1 (0-18)	5.906	4.893	0.228	7.924	3.202	0.014	0.771	2.920	0.792	-1.191	0.964	0.218
Age2 (19-39)	-2.276	0.301	0.000	7.959	5.560	0.153	15.271	3.952	0.000	0.493	0.692	0.477
Age3 (40-64)	-39.417	21.414	0.000	-46.583	28.601	0.010	-10.470	8.942	0.000	1.418	2.312	0.540
Age4 (65-84)	-47.649	35.264	0.100	-48.506	33.425	0.148	-25.448	14.463	0.000	0.160	4.056	0.969
Age5 (85+)	26.852	9.331	0.004	24.316	8.467	0.004	4.954	5.477	0.366	3.383	1.618	0.037
Gender												
Male	-22.227	9.354	0.004	-33.705	9.819	0.005	-2.091	0.857	0.013	2.432	3.544	0.493
Female	-51.118	16.876	0.008	-41.359	12.228	0.006	-9.091	1.655	0.005	1.412	4.516	0.755

Table B.16: County Characteristics of Shortage Counties with and without HPSA Designation

	Shortage Area with HPSA Designation		Shortage Area without HPSA	
	Mean	Std. Dev.	Mean	Std. Dev.
Number of Short Term Care Beds	8.59	18.47	6.79	19.38
Number of Long Term Care Beds	126.12	85.56	64.93	77.23
Number of Medicare Eligibles	2,515.92	1,603.98	2,036.36	1,192.24
Number of Medicaid Enrollees	4,686.47	2,985.12	2,808.43	2,594.76
Per Capita Income ($)	24,950.18	3,371.80	25,813.71	2,990.50
Number of People under Poverty Level	3,457.49	2,102.96	2,988.36	1,791.45
Metropolitan (%)	0.21	0.41	0.17	0.39

Note: Aside from Number of Medicaid Enrollees, which is significant only at the 5% level under the t-test, the remaining variables are not statistically significant at 1%, 5%, or 10% levels.

Figure B.1: Scatter Bin Regression - Against ACSC (1st Polynomial and 4th Polynomial)

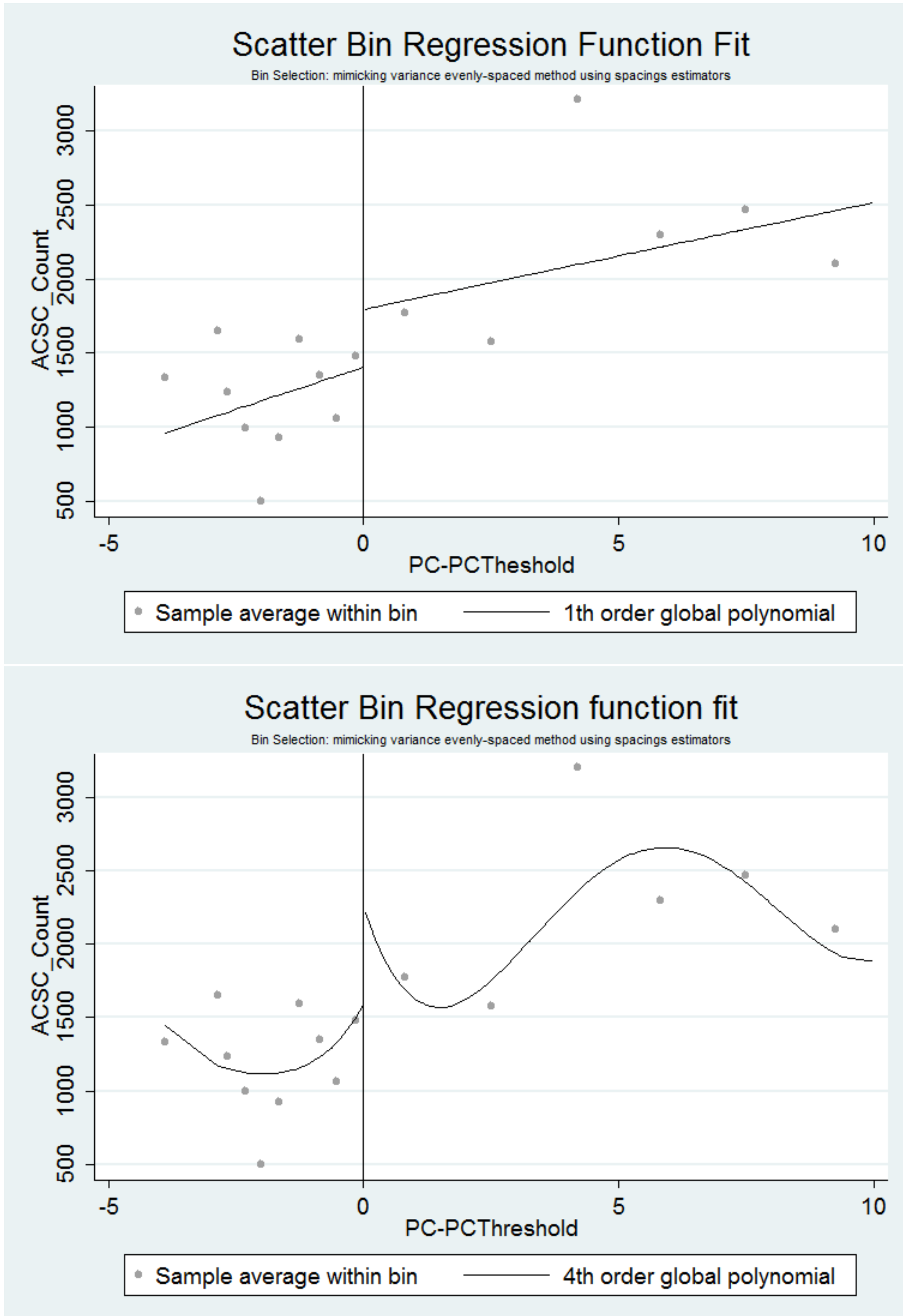


Figure B.2: Scatter Bin Regression - Against GovPolicy (1st Polynomial and 4th Polynomial)

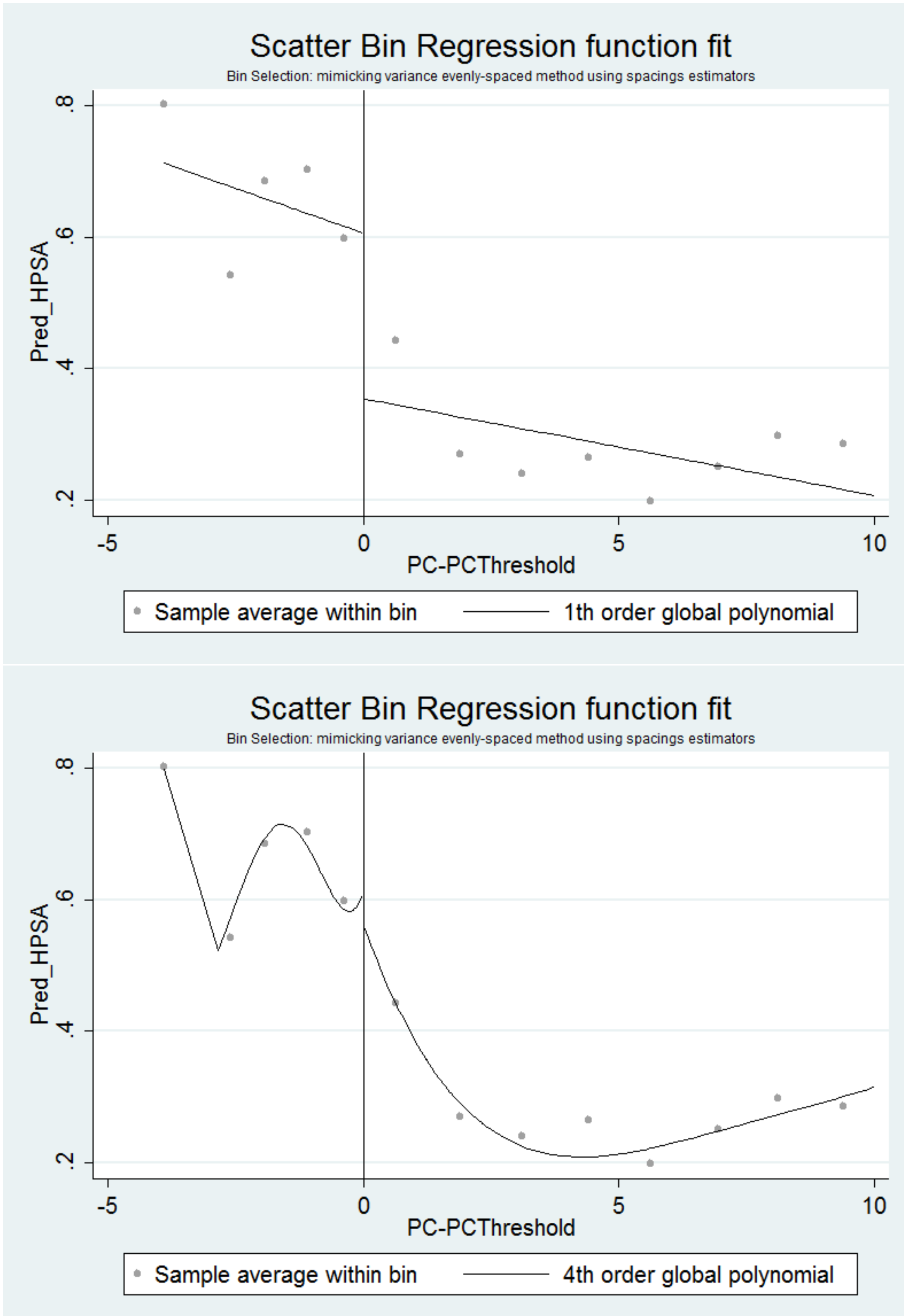


Figure B.3: Scatter Bin Regression - Difference between PC and PC threshold against number of PC in both contemporaneous and lagged time

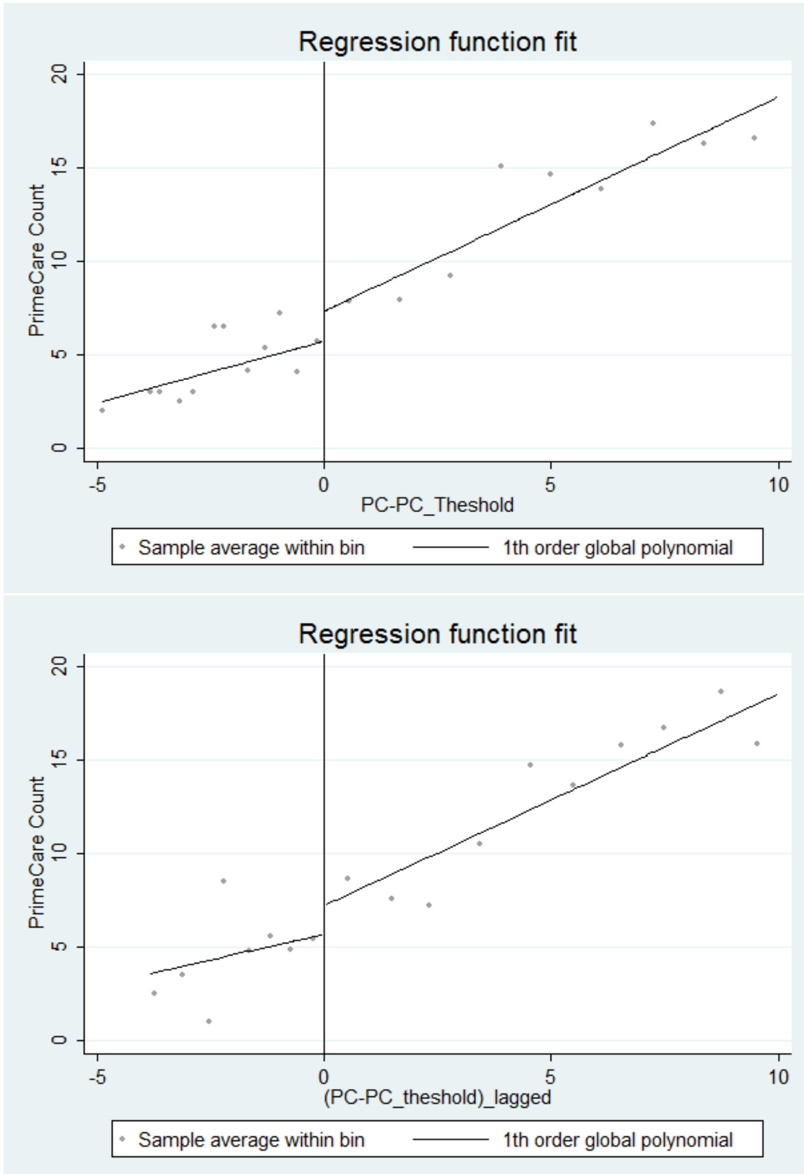
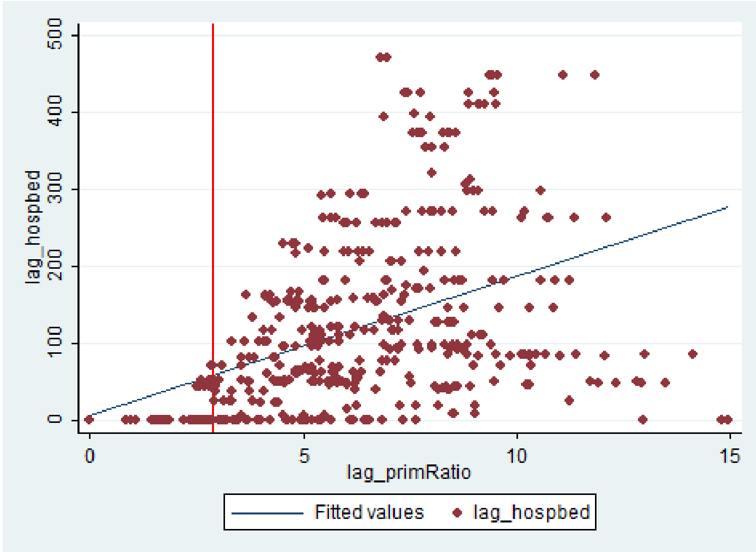
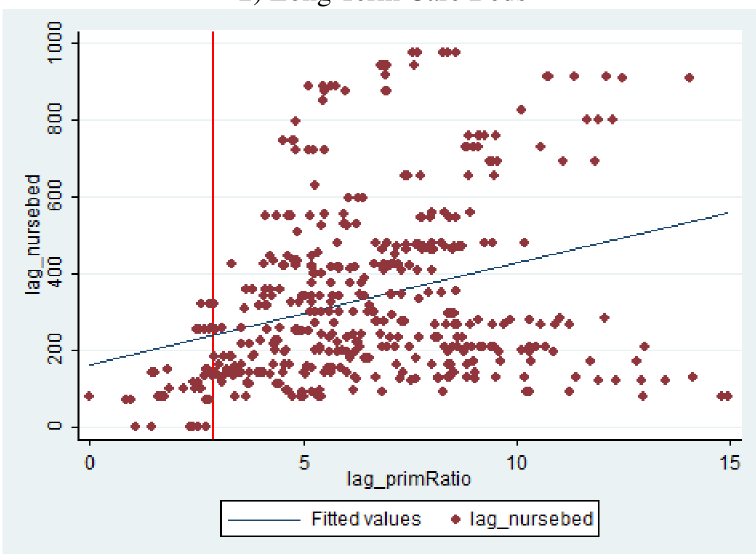


Figure B.4: Scatter Diagrams with regression For other covariates

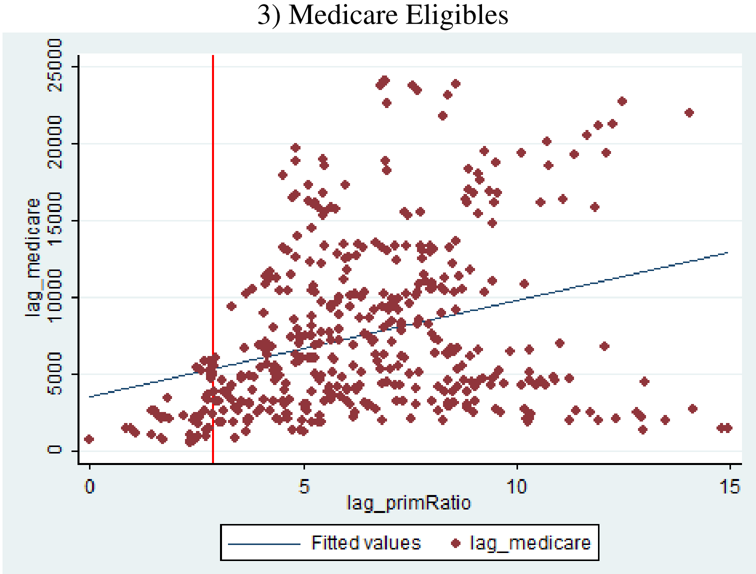
1) Short Term Care Beds



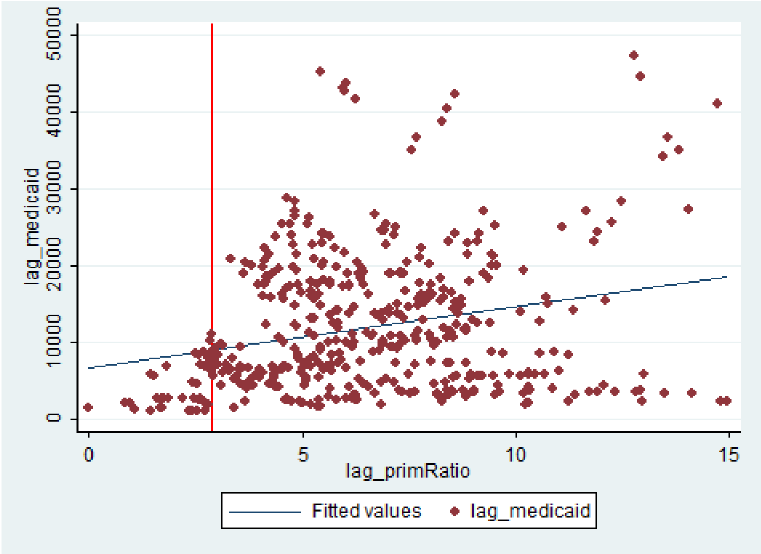
2) Long Term Care Beds



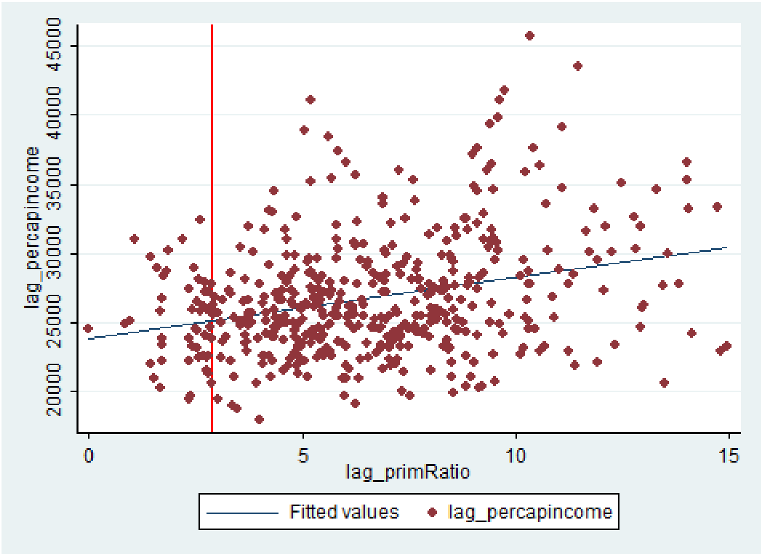
3) Medicare Eligibles



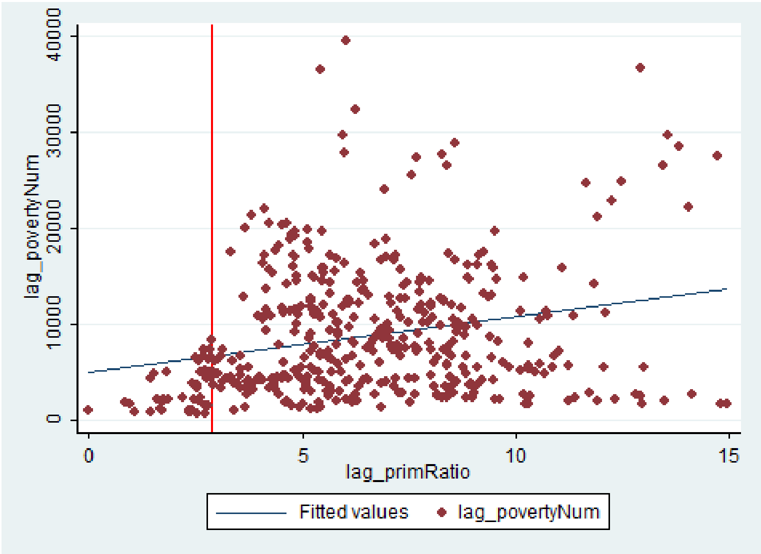
4) Medicaid Eligibles



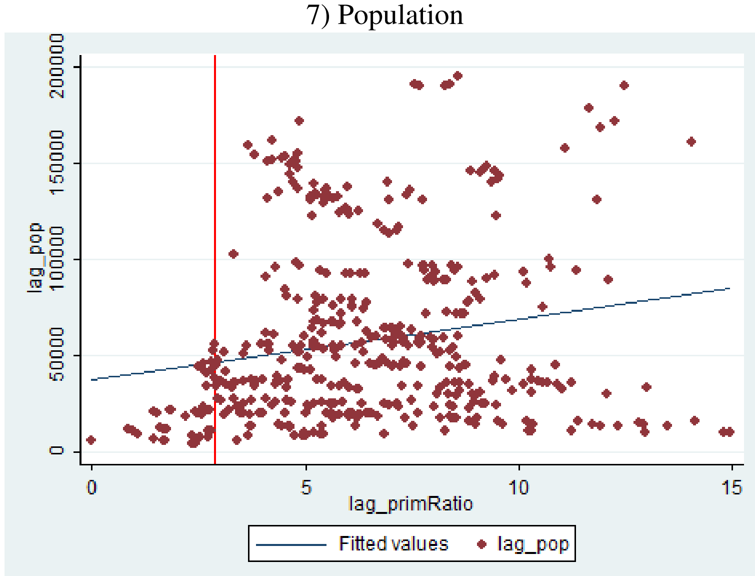
5) Per Capita Income



6) Poverty Level



7) Population



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