2019

Impact of Price, Income, and Externalities on Incentives for Health Care Providers and Patient Behaviors

Amy Ehinomen Eremionkhale
Lehigh University, amyeremionkhale@gmail.com

Impact of Price, Income, and Externalities on Incentives for Health Care Providers and Patient Behaviors

by
Amy Eremionkhale

Presented to the Graduate and Research Committee
of Lehigh University
in Candidacy for the Degree of
Doctor of Philosophy
in
Business and Economics

Lehigh University
June 2019

.

Approved and recommended for acceptance as a dissertation in partial fulfillment of the requirements for the degree of Doctor of Philosophy.

Date: June 14, 2019

Dissertation Advisor: Shin-Yi Chou

Committee Members:

Shin-Yi Chou

Todd Watkins

Mary E. Deily

Suhui Li

ACKNOWLEDGMENTS

I would like to take this opportunity to express my gratitude to the individuals who helped me with various aspects of conducting research and the writing of this dissertation. First and foremost, Professor Shin-Yi Chou for her guidance, patience and support throughout this research and the writing of this dissertation. Her insights and words of encouragement have often inspired ingenuity in me and renewed my hopes for completing my graduate education. I would also like to thank my committee members for their efforts and contributions to this work especially as it relates to excellence in writing and communicating ideas: Professor Todd Watkins, Professor Mary Deily, and Professor Suhui Li. I would additionally like to thank Professor Watkins for his guidance throughout the initial stages of my graduate career.

Contents

List of Tables

List of Figures

1 Abstract of Dissertation Chapters

1.1 Brief Abstract:

The first chapter is titled "Impact of the Change in Payments on the Actual and Perceived Behaviors of Medical Care Providers." It investigates how a change in the payments received by medical care providers affects their treatment decisions, and their behavior as perceived by their patients. A combination of the results from the income change of medical care providers, perceived changes, and actual changes in the behavior of medical care providers suggests that the decrease in income resulting from the loss of insurance coverage of the patients of the medical care providers does not lead to a statically significant shift in the actual behavior of medical care providers. However, the patients do perceive a statistically significant difference in the behavior of their medical care providers.

The second chapter is titled "The Impact of Regional Antimicrobial Use on Individual Antimicrobial Use, on Individual Health Outcomes, and on Regional Antimicrobial Resistance." This paper investigates the impact of the regional use of antimicrobials on three main areas, namely; the level of antimicrobial prescription used by individuals; an individual's interaction with the health care industry; and the level of antimicrobial resistance in the four regions as defined as Midwest, Northeast, South, and West. The results of the investigation show that firstly, there is a direct and significant relationship between the regional level of antimicrobial use and a person's use antimicrobials to treat any given condition. Secondly, the regional use of antimicrobials does not lead to a positive improvement of the individual's interaction with the health care industry. Lastly, the results of the investigation show that the use of antimicrobials in various regions leads to a significant increase of resistance levels in the regions. The magnitude at which the increase occur differ across the various regions.

The third chapter is "Impact of the Price of Physician Visit on the Use of Prescribed Medicine: A Focus on Antibiotics and the Common Cold." This paper determines the impact that the additional cost of visiting a doctor in order to obtain a prescription, has on the demand for antibiotics. This paper also investigates the behavioral responses of the medical professionals to potential negative income pressure. The results of this paper show that the individuals who use antibiotics to treat specifically the common cold are not sensitive to the price of the office based doctor visits, and are not sensitive to the price of the antibiotics.

1.2 First Chapter

First Chapter Title: Impact of the Change in Payments on the Actual and Perceived Behaviors of Medical Care Providers.

Research Question: This paper asks if and how medical care providers change their treatment plans when there is a change in the income they receive from their patients. Taking this question further, this paper asks if there are any changes in the patients' perception of the behaviors of their medical care providers, as the income received by the medical providers change. This paper investigates how a change in the payments received by medical care providers affects their treatment decisions, and their behavior as perceived by their patients.

Motivation: This paper is motivated by the current political discourse to remove the individual mandate instituted by the Patient Protection Affordable Care Act (PPACA). Before the Patient Protection and Affordable Care Act (PPACA) was enacted into law in 2010, young adults who were not full-time students aged out of their parents' insurance plans when they turned 19 years old. This age-out policy was true for both private insurance coverage and Medicaid coverage. Existing literature shows that there exists a sharp drop in insurance coverage rates that results from young adults "aging out" of their parents' insurance plans (Andrews, 2013) (Palmieri, 2017). There is also a significant decrease in the per-visit income received by medical care providers when a patient is uninsured versus insured (Anderson et al., 2012).

Therefore, as the push to repeal the individual mandate has been successful, it follows that the proportion of uninsured individuals in the population will increase, and thus the need to understand the potential impact of this policy change on both the supply-side and demand-side of medical care becomes a matter of utmost concern.

Data: This research uses office based visit level Medical Expenditure Panel Survey (MEPS) data for the analysis. It spans the years 1996 through 2009, where 1996 is as far back as the available MEPS data goes, and the effects of the PPACA that affect the aging-out policy began in 2010. The sample excludes full-time students, married individuals, and office-based visits with total payments to the provider that exceed the 95th percentile.

Empirical Methodology: This paper uses the regression discontinuity (RD) design to exploit the sharp discontinuity in insurance coverage that occurs at the age of 19, induced by the aging-out policy induced, to investigate the impact of the significant decrease in the total income on the behavior of medical care providers. In the model, age is measured in months, where a 19 year old is 228 months old. The bandwidth used in the model is 12 months around the threshold of 228 months. The change in insurance coverage is measured directly through the change in per-visit income sourced from either private insurance or from Medicaid payments for services. The demographic variables are smooth across the threshold of 228 months which allows for the proper identification of the causal effects of interest in the RD model. The model also controls for year and region indicator variables.

Results: There exists a statistically significant reduction in the income received by the medical care providers from private and Medicaid source, across the threshold of 228 months of age. The decrease in the per-visit income from those sources is 16.4%. There does not appear to be a significant shift in the treatment plan of the providers from the relatively more time consuming diagnostic test and methods, to a time saving method of relying more heavily on lab tests as a diagnostic tool. Patient's do perceive a change in the behaviors of their medical care providers, across this threshold of 228 months of age. A combination of the results from the income change of medical care providers, perceived changes, and actual changes in the behavior of medical care providers suggests that the decrease in income resulting from the loss of insurance coverage of the patients of the medical care providers does not lead to a statically significant shift in the actual behavior of medical care providers. However, the patients do perceive a statistically significant difference in the behavior of their medical care providers.

1.3 Second Chapter

Title: "The Impact of Regional Antimicrobial Use on Individual Antimicrobial Use, on Individual Health Outcomes, and on Regional Antimicrobial Resistance."

Research Question: This paper investigates the impact of the regional use of antimicrobials on three main areas, namely; the level of antimicrobial prescription used by individuals; an individual's interaction with the health care industry; and the level of antimicrobial resistance in the four regions as defined as Midwest, Northeast, South, and West, by the United States Census Bureau defines the four statistical regions.

Data: The primary source of data in this the Medical Expenditure Panel Survey (MEPS) dataset, over the years 2002 through 2012. MEPS provides data on antimicrobial use, health outcomes, health expenditures, and individual demographic information. The secondary sources of data include the National Antimicrobial Resistance Monitoring System (NARMS). NARMS provides data on regional antimicrobial resistance levels over the years.

Empirical Methodology: The econometric framework of this analysis is a two stage least squares (2SLS) model, where the instrumental variable is the one period lagged yearly regional average of antimicrobial use for any given condition. This instrument is for the yearly regional average of antimicrobial use for any given condition, the key dependent variable in the model.

Results: The results of the investigation show that firstly, there is a direct and significant relationship between the regional level of antimicrobial use and a person's use antimicrobials to treat any given condition. This implies the presence of a negative externality on any particular individual in the various regions, especially in the regions with relatively high antimicrobial use. Secondly, the regional use of antimicrobials does not lead to a positive improvement of the individual's interaction with the health care industry. This indicates that the extent of antimicrobial use in the various regions is improper. Lastly, the results of the investigation show that the use of antimicrobials in various regions leads to a significant increase of resistance levels in the regions. The magnitude at which the increase occur differ across the various regions.

1.4 Third Chapter

Title: "Impact of the Price of Physician Visit on the Use of Prescribed Medicine: A Focus on Antibiotics and the Common Cold."

Research Question: This paper determines the impact that the additional cost of visiting a doctor in order to obtain a prescription, has on the demand for antibiotics. This paper also investigates the behavioral responses of the medical professionals to potential negative income pressure.

Motivation: The analysis of Cantrell et al. suggests that around 11 million of prescriptions in the USA are inappropriate and estimates a waste of health care resources up to US$ 281 millions. Filippinia et al. (2003) With the recently enacted Patient Protection Affordable Care Act (PPACA), there is increased potential for moral hazard, and access to care and prescribed medications for a large number of the population, where the cost of medical care has decreased for these individuals. As a result of this increased moral hazard, it is reasonable to question the impact of the increased medical access on the problem of Antimicrobial Resistance. To address one element of that question, this paper estimates the impact of the price of a doctors visit on the demand for antibiotics.

Data: The analysis of the derived demand model in this paper will be done using the Medical Expenditure Panel Survey (MEPS). This data set is a nationally representative survey of the US civilian, non-institutionalized population. The data used span the years 2004 through 2010, however it is pooled, and thus no special econometric treatment was used to take advantage of the length and panel structure of the data.

Empirical Methodology: The analysis done in this paper uses a demand equation for the prescription medication, antimicrobials, using a Probit model. The dependent variable in this equation is a dichotomous variable that equals one for individuals who used the antibiotics as a course of treatment for the common cold. Among other independent variables included in this analysis, the key independent variable here is the the average total price of office based visit made to the doctor.

Results: The results of this paper show that the individuals who use antibiotics to treat specifically the common cold are not sensitive to the price of the office based doctor visits, and are not sensitive to the price of the antibiotics. The probability of receiving antibiotics for the treatment of the common cold responds to the change in neither the price of the medication itself nor the price of the office-based doctor visit. It also suggest that the impact of gaining insurance on the demand for antibiotics is neither large nor statistically significant.

2 Chapter 1: Impact of the Change in Payments on the Actual and Perceived Behaviors of Medical Care Providers

2.1 Introduction

The recent repeal of the individual mandate of the Patient Protection Affordable Care Act (PPACA) which was implemented in 2010, has made it important to study the impact of having and then losing health insurance coverage on both patients and providers. This paper investigates how a change in the payments received by medical care providers affects their treatment decisions, and their behavior as perceived by their patients. Patients' perspectives on their medical treatment experience have received considerable prominence in the evaluation of modern healthcare, with these subjective appraisals being viewed as valuable health outcomes. (Boquiren et al., 2015; Kupfer and Bond, 2012; Squires, 2012; Riiskjær et al., 2010; Freeman, 2002)

To carry out this analysis, I take advantage of the pre-2010 law specifying that young adults aged out of their parent's insurance plan at the age of nineteen. Existing literature shows that there was a sharp drop in their insurance coverage rates (Andrews, 2013; Palmieri, 2017). I use the loss of insurance coverage as a natural experiment that allows for the identification of the change in the payments received by their medical care providers.

I study the treatment and perceptions of a sample of unmarried young adults, excluding full time students, from the Medical Expenditure Panel Survey (MEPS).

The sample period begins in 1996, the earliest year available, and ends in 2009; the year before the 2010 Affordable Care Act.

I first establish that although the total payments received by the providers did not change, the amounts received from the different payment sources changed, as the young adults' aged-out of their parent's insurance. I use regression discontinuity to correct for possible endogeneity of provider payments. Provider payments maybe endogenous because it is likely correlated with unobserved provider and patient preferences. However, the aging-out policy exogenously determines the insurance status of the patients which affects how medical treatments will be paid. This change in status is not related to the physicians preference or patient preference, but rather is determined by the natural process of aging and therefore is an exogenous shock to the payments received by providers. I then investigate the impact of the change in the provider's payments on their treatment decisions and on the patients' perception of the providers' behavior.

In the regression discontinuity framework, I compared the treatment and experiences of those who are just above nineteen to those of the young adults just below nineteen, because these two groups should be very similar within a narrow bandwidth. To confirm the similarity between the two groups I performed a smoothness test of other characteristics within a bandwidth of twelve months just above and just below the age of nineteen. The observable characteristics are smooth across the threshold of age nineteen, as discussed in below.

This paper makes three contributions to the current literature on how changes in providers' payments affect their treatment decisions. I find that although there are statistically significant changes in the amount paid to the providers' payments from the different sources, there is no statistically significant change in the providers' treatment decisions. Secondly, this paper contributes by investigating the patients' perception of their providers' behaviors. I find that there is a statistically significant change in the patients' perception of their providers' behaviors as the payments made to their providers change. This change in perception is for the worse, as patients perceive that their providers are less respectful of them, spend less time with them, and do not listen to them as much as they did before the change in the providers' payments. This contribution is important because these changed perceptions may affect trust and follow up in the treatment plan. Finally, I make a methodological contribution in applying regression discontinuity to examine the causal relationship between the payments received by providers from the different sources, the treatment decision of the providers, and their patients' perception.

The rest of the paper is organized as follows; Section 2.2 discusses the dataset and how the analysis sample is built. Section 2.3 presents the empirical framework and discusses the identification strategy. Section 2.4 discusses the results of the analysis. The robustness checks of these results are reported and discussed in Section 2.5. The discussion and summary of this paper are in Section 2.7. The figures and tables for this paper are at the displayed end the paper, after the references.

2.2 Data

2.2.1 Data Description

I use data on individual office visits from the Medical Expenditure Panel Survey (MEPS) for the analysis. The Medical Expenditure Panel Survey (MEPS) is a set of large-scale nationally representative surveys of families and individuals, their medical providers, and employers across the United States (AHRQ, 2009), and is the most complete source of data on the cost and use of health care and health insurance coverage available. MEPS has been used extensively in scientific publications and published reports, as well as by the Federal and state governments to examine the delivery and financing of health care in the United States (Cohen et al., 2009; AHRQ, 2018; Wang et al., 2006).

I use data from two of the MEPS surveys: a household survey and a survey of medical providers (provider refers to a combination of Physicians and Non-Physicians, e.g. RN, LPN, PA, etc.) The Household Component[1] collects data from a new panel of sample households each year. The data for each panel is collected over two calendar years, in five rounds of interviews. Each round of MEPS-HC interviews collects information pertaining to a specific time period called a reference period (AHRQ, 2015; Cohen et al., 2009; Harrison et al., 2018).

[1]This component results from the household survey. Other event files are Dental Visits files, Other Medical Expenses files, Hospital Inpatient Stays files, Emergency Room Visits files, Outpatient Visits files, Prescribed Medicines File, Home Health files, Appendix to MEPS Event files (AHRQ, 2017).

The Office-Based Medical Provider Visits File [2] provides detailed information on office-based provider visits for a nationally representative sample of the civilian non-institutionalized population of the United States (AHRQ, 2014). I combine data from these two survey files using the person identifier, DUPERSID, for each year to develop my sample.

2.2.2 Analysis Sample

The sample pools data from 1996, the earliest available data through 2009, the last year before the implementation of the PPACA. I extract data on unmarried young adults who are not full-time students because the age-out policy did not apply to full-time students (Healthcare.gov, 2012; Anderson et al., 2012).

I am able to measure the age of the young adults used in my analysis in months because MEPS data include the birth month and year of each patient as well as the month and year in which each office-based visit occurred. In the 14 year sample, there are 7,912 office-based visits occurring within the bandwidth of 12 months on either side of age 228 months for the young adults. The threshold age is 228 months (19 years $\times$ 12 months), with observations on young adults in the age range of 216 months and 240 months.

Each observation in the sample represents one office visit, and includes informa-

[2]The Office-Based Provider Public Use Data File contains characteristics associated with the office-based visit, such as, date of the visit, time spent with the provider, types of treatment and services received, types of medicine prescribed , condition codes , expenditures, and sources of payment associated with the visit (AHRQ and Quality, 2014).

tion on the demographics of the patient, the ICD9 condition addressed during that visit, and the payments for care provided, including out-of-pocket payments, payments by private insurance, Medicaid, and other sources. In an effort to minimize the influence of outliers, I exclude visits with total payments greater than \$300, which represented the approximate value for the 95^{th} percentile of the total payments.

2.3 Empirical Framework and Estimation

2.3.1 Empirical Framework

The following model is estimated by OLS. The bandwidth is limited to twelve months around the age 228 months threshold, and the regressions take the form:

$$\begin{aligned} Y_{ivrt} &= \alpha_0 + \alpha_1\, AO_{ivrt} + \alpha_2\, AO_{ivrt} \times (age_{ivrt} - 228\text{months}) \\ &+ \alpha_3\,(1 - AO_{ivrt}) \times (age_{ivrt} - 228\text{months}) + \delta\, X_{ivrt} \\ &+ \text{ICD9-CCI-0}_{ivrt} + \alpha_t + \alpha_r + u_{ivrt} \end{aligned} \tag{1}$$

where Y represents an outcome or treatment measures for patient i at visit v in region r in year t. The treatment measures are the payments received by the medical care providers. The total payments received by the provider for each office-based visit are comprised of payments from different sources, including: private insurance, Medicaid, out-of-pocket (from the patients), and other sources. The second measure of payments I use in this analysis, is the sum of the amounts received from private insurance and Medicaid for each visit. This is because the age-out policy affected young adults with coverage from either their parent's private insurance or coverage from Medicaid. In addition to these total payment values, I include the payments received by the providers separated by source in order to better analyze the nuanced changes occurring in the providers' payments. The summary statistics of these variables are shown in the section of table 1.

The outcome variables are comprised of the provider treatment decision measures and the patient perception measures. The provider decisions measured are indicator variables: "Any Medicine Prescribed", "Lab Tests", and "Other Diagnostic Test/Exam". Respectively, these variables equal one if medicine was prescribed during the visit, or lab tests were done during the visit, and other relatively more time consuming diagnostic tests/exams[3] were performed during the office-based visit.

The patients' perception outcome measures are indicator variables: "Enough Time", "Listen", and "Respect", that equal one if the patient reported that the provider spent enough time with them during the visit, listened to them, and showed them respect during the office-based visit.

AO stands for Age-Out and is an indicator variable that equals one if the individual i is older than 228 months at time of the visit v. The estimated coefficient of this variable, α_1, represents the estimated discontinuity of interest at the age threshold for each of the outcome and treatment variables.

The variable *age* represents the age of the individual i at year t of the visit v measured in months.[4] The use of the month unit of measure is appropriate for this

[3]Tests/Exams other than lab-tests, such as in-depth physical exams, and intricate personal information (and behavior) gathering - questioning

[4]Given the bandwidth of twelve months, the individuals in the main analysis are aged 216

study because many private and some public health plans cover dependents through the last day of the month in which the dependent turns 228 months (Anderson et al., 2012; Collins et al., 2008).[5] Separate age trend terms above $[(AO_{iv}) \times (age_{iv} - 228\text{months})]$ and below $[(1 - AO_{iv}) \times (age_{iv} - 228\text{months})]$ the age cutoff are included in the model and parameterized so that $\alpha_2 = \alpha_3$ if the trend is the same above and below the cutoff (Almond et al., 2010).

X_{iv} is a vector of the demographic variables for each individual in the sample. The demographic variables used in this analysis are: race (equals one if the patient is White and zero otherwise), gender (equals one if the individual is female, and zero otherwise), ethnicity (equals one if the patient is Hispanic and zero otherwise). Also includes: employment status (equals one if the patient is employed, either full-time or part-time employed and zero if unemployed), marital status (equals one if patient is married and zero otherwise[6]), and the personal income of each individual in the sample.

The conditions treated in each visit are represented using International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) condition codes which have been aggregated into clinically meaningful categories that group simi-

---

months, 217, 218, ..., 228 months, 229, 230, ..., and 240 months at the time of the office-based visit.

[5]A detailed discussion of the Regression Discontinuity (RD) design and its related issues is put forward in Imbens and Lemieux (2008) and Lee and Lemieux (2010).

[6]The other categories that comprise of other than married, are Separated, Divorced, Widowed, and Never Married.

lar conditions (CCCODEX) (AHRQ, 2008b)[7]. These conditions are grouped using the Charlson Commorbodity Index (CCI) where the indicator variable, *ICD9-CCI-0*, equals one for the observations for CCI value of zero, and zero for observations with CCI values greater than zero, which in the case of this sample is the value of one. (Roffman et al., 2016). Finally, the model also includes the year (α_t) and region (α_r) fixed effects. The regions in the sample are Northeast, Midwest, South, and West.

All estimations of equation 9 are weighted using the final person weight, called PERWTF in the household component data of MEPS. The standard errors are clustered by ages, which are measured in months (Lee and Card, 2008).

The reduced form estimates of the direct impact of the AO_{iv} indicator on the treatment and outcome measures are reported separately. This paper identifies the causal effect of the change in payments on the actual and perceived behaviors of medical care providers by combining the outcome and treatment estimates (Almond et al., 2010).

In the language of instrumental variables, the discontinuities in actual provider behavior and patient perceived provider behaviors are the reduced-form estimates and the discontinuity in provider payments is the first-stage estimate. There are several ways to compute the IV estimator (Cameron and Trivedi, 2017). I compute

[7]ICD9 codes are The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) is the U.S. health system's adaptation of international ICD-9 standard list of six-character alphanumeric codes to describe diagnoses. ICD-9-CM contains a list of codes corresponding to diagnoses and procedures recorded in conjunction with hospital care in the United States (Rouse, 2014).

the estimator as:

$$\beta = \frac{\frac{dy(\text{outcome})}{dz}}{\frac{dy(\text{treatment})}{dz}} = \frac{\frac{d(\text{“Any Medicine Prescribed”})}{d(AO)}}{\frac{d(\text{payments})}{d(AO)}}$$

$$= \frac{\alpha_1(\text{“Any Medicine Prescribed”})}{\alpha_1(\text{payments})} \tag{2}$$

where β is the effect of the change in the providers' payments on the actual and perceived behaviors of the providers. The reduced form estimate of the effect of turning 228 months on the various outcome variables (for instance, the "Any Medicine Prescribed" variable), $dy(\text{outcome})/dz$, is divided by $dy(\text{treatment})/dz$, the reduced form estimate of the effect of turning 228 months on the treatment variable: the medical care providers' payments.

In this framework, the instrument is the AO indicator. For the AO indicator to be a valid instrument, there must exist a strong first-stage relationship between the AO indicator and the measure of the per-visit provider revenue; note that this relationship will be conditional on our running variable (age in months). Also, the exclusion restriction requires that the only mechanism through which the instrument AO indicator affects the actual provider behaviors and patient perception outcomes, conditional on age-in-months falling within the bandwidth, is through its effect on the provider's payments (Cameron and Trivedi, 2017; Almond et al., 2010; Schmidheiny, 2018).That is, the only way turning 228 months years old affects actual and perceived medical provider behavior is through its effect on the providers' payments.

2.3.2 Smoothness Criteria

The existence of smooth observable characteristics validates the exclusion restriction, where the discontinuous change in revenue we observe at the age threshold is due only to the discontinuous change in insurance status at age 228 months and not due to any discontinuous changes in other characteristics (Anderson et al., 2012; Almond et al., 2010; Lee and Lemieux, 2010; Imbens and Lemieux, 2008). The regression discontinuity design requires the assumption that no other variables change discontinuously at the age of 228 months threshold (McCrary, 2007; Zuckerman et al., 2006; Trochim, 1984).

These continuity assumptions might not be plausible if the young adults were able to manipulate the running variable; their age (McCrary, 2007; Almond et al., 2010; Anderson et al., 2012). However, the age of the young adults cannot be reasonably manipulated because we measure age at the monthly level in our analyses (Anderson et al., 2012). This fact implies that most obvious confounders particularly high school graduation or commencement of employment, should not bias the estimates. For example, high school graduations occur in June, but nineteenth birthdays are distributed throughout the year. Thus, the high school graduation rate should not change discontinuously in the month following an individual's nineteenth birthday. Table 2 and Figure 1 show the check of smoothness. The last two columns of table 2 show that smoothness of these factors exists in this paper's analysis. That is, the observable characteristics of the young adults measured and conditions treated are similar for the group of patients on either side of the 228 month threshold. These columns report regression coefficients and standard errors (SE) from making the observable characteristics the Y variables in equation 9.

The lack of a significant difference in the observable characteristics and further the unobservable characteristics between the two groups of individuals shows the comparability at the baseline around the cutoff age of 228 months.

2.4 Results

Figure 2 shows the payments by sources received by the medical care providers around the 228 month threshold. The figures show that there is no obvious change in the total payment received by the providers for each visit. There does, however, appear to be a significant decrease in the total amount received from private insurance and Medicaid sources combined. The largest change appears to be the decrease in the amount sourced from private insurance. The payments received from the out-of-pocket source of the patients visually shows a jump across the threshold.

Figure 3 presents the three measures of the providers' actual treatment decisions around the age threshold. There is no obvious increase or decrease in the measures of the providers' treatment decisions. Figure 4 represents the three variables for the patients' perception of their providers' behavior. Here, there does appear to be a clear decrease for all three variables, across the threshold. Inspection of these figures reveal that there may be strong effects in the payments and the patients perceptions, but not in the actual treatment decisions.

2.4.1 Change in Medical Providers' Payments Across Threshold - Treatment Variable.

The estimated impact of aging out on payment sources is shown in Table 3. The results show that there is a statistically significant decrease in the sum of the payments received by medical care providers sourced from private insurance and Medicaid in the amount of \$7.61 across the age threshold. This implies a 16.33% ($\frac{7.614}{46.60}$) reduction in the payments compared to a mean of \$46.60 for the twelve months below the threshold (the "untreated" group in this regression discontinuity design). The total payment from all sources received by the providers does not change statistically significantly as the young adults age out of their parents' insurance coverage.

There is a statistically significant increase in the medical providers' per-visit revenue sourced from the out-of-pocket payments made by the patients, in the amount of \$5.77. This amount represents a 45.87% increase compared to the mean of \$12.58 for the twelve months before the age 228 month threshold. The payments sourced from private insurance decreased statistically significantly by \$9.986. This decrease is a 37.96% drop in the payment sourced from private insurance, compared to the "before" average of \$26.31. There is no statistically significant change in the amounts received from the other payment sources. These results are supported by the findings in previous literature on the drop in insurance coverage that occurs across the threshold of age 228 months (Anderson et al., 2012).

Therefore, when there is a loss of insurance coverage induced by the natural experiment (aging-out policy), the medical care providers do not lose a statistically significant amount of their total per-visit revenue. However, the patients pay 45.87%

more money out of pocket than they did before aging out, and payments from private insurance companies decrease by a statistically significant 37.96%.

2.4.2 Change in the Providers' Treatment Decisions

Table 3 presents the estimates of changes in three provider treatment decisions: "Any Medicine Prescribed", "Lab Tests", and "Other Diagnostic Test/Exam". On average, providers prescribed medicine during 28.58% of their office-based visits, as shown in Table 1. The estimated change in the prescribing behavior of medical care providers across the threshold is -0.036. This result is not statistically significant, which implies that there is no discontinuous change in the prescription behavior of medical care providers across the age threshold of 228 months.

The mean of the second treatment variable is 0.2425, which implies that a lab test occurred for 24.25% of the visits in the sample, as shown in Table 1. The estimated change in the occurrence of lab tests across the threshold is -0.039, and is not statistically significant. This result implies that providers do not change their treatment behavior as it relates to the number of visits where lab tests are performed.

The mean of the third variable "Other Diagnostic Test/Exam" shows that in 11.24% of the visits (as shown in Table 1), some diagnostic test or exams other than lab tests were performed. The estimated change in the occurrence of other diagnostic test and exams during an office-based provider visit is -0.045 with a standard error of 0.036. It is therefore, not statistically significant. That is, medical care providers did not significantly decrease their use of other diagnostic test and exams during visits, across the age threshold.

Overall, medical care providers do not change their treatment decisions as their patients age across the threshold of 228 months.

2.4.3 Patient Perception of Change in Providers' Behaviors

The mean of the first patient perception variable, "enough time", is 40.82% (Table 1). The estimated change in this variable across the age 228 months threshold is -0.079 percentage points with a standard error of 0.031, making it statistically significant at the 5% level of significance, as shown in Table 3. This statistically significant decrease represents a 19.59% ($\frac{0.079}{0.4033}$) decrease relative to the mean of 40.33% from the twelve months prior to 228 months.

The mean of the second variable "Listen" shown in Table 1, indicates that patients felt that they were listened to in 44.52% of the office-based visits. The estimated change in this patient perception variable is -0.105 percentage points with a standard error of 0.028, which is statistically significant at the 1% level of significance. This estimate represents an approximate decrease of 24.22% in the visits where patients felt the provider listened listen to them, relative to the average of 43.36% from the twelve months below the threshold.

The mean of the third variable, "Respect", shown in Table 1 is 46.21%. The estimated change in this perceived variable is -0.091. It is statistically significant at the 5% level of significance. The estimate represents an approximate decrease of 20.09% in the visits where providers felt respected by their provider, relative to the below 228 month threshold average of 45.30%.

Overall, the results reported in table 3 show that across the threshold of age 228 months, patients felt significantly less satisfied with their provider's behavior. Once they turned 19, the patients felt that the medical providers spent less than enough time with them, they felt less respected, and they felt the providers did not listen to them as much.

2.4.4 Impact of the Change in Provider Payments on the Actual and Perceived Behavior of Medical Care Providers

This section discusses the analogous instrumental variable estimates, β, which are reported in table 4. It reports on the impact that the changes in the providers' payments by sources has on the actual and perceived behaviors of the provider, across the discontinuity. All specifications include before and after trends, year trends, conditions, and other covariates. The estimated changes are reported for a \$10 change in the payments received by the provider.

The first three columns of table 4 show the effect of the change in total payment on the actual treatment decisions of medical care providers. The standard errors of these βs are derived using the propagation of error (Chemistry-LibreTexts, 2018).[8] The last three columns of table 4 show the effect that the change in the providers' payments by each source, has on the patients' perception of their provider's behavior.

The results show that a \$10 decrease in total per-visit payment does not lead to

[8]Propagation of Error (or Propagation of Uncertainty) is defined as the effects on a function by a variable's uncertainty. It is a calculus derived statistical calculation designed to combine uncertainties from multiple variables, in order to provide an accurate measurement of uncertainty.

statistically significant change in any of the measured provider's treatment decisions. The total payment for each visit received by the medical care provider is the only payment measure used to investigate the impact on the actual treatment decision of the providers.

A $10 decrease in the payments from the sum of private insurance and medicaid sources leads to a statistically significant decrease of 0.1038, 0.1379 and 0.1195 percentage points in the visits where the young adults felt that their provider spent enough time with them, listened to them and respected them, respectively. This result is driven by the estimated change in private insurance payments.

An increase of $10 in the patients' out-of-pocket payments received by the provider leads to a statistically significant decrease in the visits where patients' felt their provider spent enough time with them by 0.1369 percentage points. The results show that there is a statistically significant decrease of 0.1819 percentage points in the visits where patients felt listened to and a statistically significant decrease of 0.1577 percentage points in the visits where patients felt respected by the providers, as the payments they made out-of-pocket to their providers increased by $10.

In sum, there is no change in the providers' actual treatment decisions as the payments from the various sources change. However, the patients perceive a difference in the behavior of their medical care providers, as the sources of the payments received by the providers change.

2.5 Robustness Checks

In this section, I discuss the sensitivity of my results to alternative bandwidths (section 2.6), and the sensitivity of the results to the outliers of the payments limits (section 2.6.1).

2.6 Bandwidth Sensitivity

The OLS estimates of the treatment and outcome variables are qualitatively the same for a wide range of bandwidths. Table 5 repeats the results for a twelve-month bandwidth, then reports the estimates with nine-month and fifteen-month bandwidths.

Overall, the estimated discontinuities shown in table 5 are qualitatively similar across the nine month to 15 month bandwidth. When the bandwidth is nine months, the change in the total payments is $-\$2.165$, the change in payments sourced from private insurance and Medicaid combined is $-\$9.052$, the change in out-of-pocket payments is $\$4.917$, and the change in payments sourced from private insurance is $-\$10.255$. When the bandwidth expands to fifteen months on either side of the threshold, the total payments, the payments sourced from Medicaid and private insurance combined, the out-of-pocket payments, and the private insurance payments change by $\$1.327, -\$7.046, \$5.366$, and $-\$10.366$, respectively. These are similar to the changes estimated with the main bandwidth of twelve months.

2.6.1 Outlier Sensitivity

Changing the limit with which I determined the outliers removed from my analysis sample does not change the qualitative estimates of the treatment and outcome variables using the reduced form equation 9. In table 6, I show that these point estimates for an analysis sample without the outliers in the 80^{th} percentile (approximately \$100) and the 90^{th} percentile (approximately \$200) of the total payment variable, are qualitatively similar.

2.7 Discussion

This paper finds that there is a statistically significant drop by 16.33% in payments that results from the drop in private and public (Medicaid) insurance coverage, with the drop of 37.96% in payments sourced from private insurance. On the other hand, there is a statistically significant increase of 45.87% in the out-of pocket source of payment. These results are reflective of the drop in insurance coverage among the young adults occurred due to young adults aging out of their parents insurance at age 228 months (Collins et al., 2008; Schwartz and Damico, 2010; Palmieri, 2017). Despite the change in the sources of the total payment, my results showed that there was no change in the actual treatment decisions of the medical care providers. However, my further results indicate that patients did perceive a change in the behavior of their medical care providers, namely, the patients felt that their providers did not spend enough time with them, the patients felt less respected, and the patients felt less listened to by their medical care providers.

Combining the results from the reduced form estimates of the treatment and outcome variables allowed for the causal estimation of the effect of the change in payments on the actual and patient-perceived behaviors of the medical care providers. As the mix of the payments received by medical care providers changed, their actual treatment decisions did not change. However, the patients' perception of their providers' behaviors changed as these payment sources changed. Implying that the patient's expected more from their medical care providers as the out-of-pocket payments they made increased.

The relatively recent repeal of the individual mandate portion of the Patient Protection and Affordable Care Act (PPACA) will allow for a drop in the level of private health insurance coverage that currently exists in the economy, mostly from the non-elderly adult population, of which the nineteen year old's are a relevant proxy (Anderson et al., 2012). This would, as estimated in this paper, thus lead to significant changes in the sources of the payments received by medical care providers. Therefore, given that the patient's perception of their providers is increasingly considered a cornerstone of effective health care delivery (Clever et al., 2008), my results shown and discussed above highlight the importance of considering how these patient perceptions change as the payment structure of their medical care providers' changes.

Table 1: Sample Summary Statistics

	Entire Sample		Before 228 Months	
	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)
Payment Variables:				
Total Payment From All Sources ($)	67.31	57.99	68.85	57.38
Total Payment from Private Insurance & Medicaid ($)	42.72	53.92	46.60	54.98
Payment by Sources:				
Out-of-Pocket ($)	14.68	33.74	12.58	28.56
Private Insurance ($)	21.96	42.84	26.31	46.12
Medicaid ($)	20.84	44.58	20.43	44.40
Others ($)	9.83	31.75	9.53	31.27
Outcome Variables - Treatment Decisions:				
Any Medicine Prescribed	0.2859	0.45	0.2998	0.46
Lab Tests	0.2425	0.43	0.2331	0.42
Other Diag Test/Exam	0.1124	0.32	0.1179	0.32
Outcome Variables - Patients' Perception:				
Enough Time	0.4082	0.49	0.4033	0.49
Listen	0.4453	0.50	0.4336	0.50
Respect	0.4621	0.50	0.4530	0.50
Control Variables:				
Female	0.6527	0.48	0.6342	0.49
Nonwhite	0.1830	0.39	0.1819	0.39
Hispanic	0.2781	0.45	0.2514	0.43
Employed	0.7424	0.44	0.7243	0.45
Personal Income	7521	8314	6239	7037
ICD9-CCI-0	0.97	0.93	0.98	0.94

Notes: The number of observations for the entire sample is 7912, and for the sample before 228 months is 3826.

Table 2: Means Before & After Cutoff: Smoothness Tests

	Mean Below Cutoff	Mean After Cutoff	Regression estimates of discrete jump at 228 months (1 year bandwidth)	S.E. for difference estimates in RD
	(1)	(2)	(3)	(4)
Female	0.63	0.67	0.03	[0.032]
Nonwhite	0.18	0.18	-0.01	[0.022]
Hispanic	0.25	0.29	0.04	[0.024]
Employed	0.72	0.76	0.04	[0.035]
Personal Income	6239	8722	150.62	[676.38]
ICD9-CCI-0	0.98	0.96	0.00	[0.010]

Notes. The standard errors are clustered at the age level, measured in months. The differences and their related standard errors are estimated using McCary (2008), by regressing each of these demographic variables in the same framework as our regression disconuity estimates. These difference estimates are also weighted using the individual sample weights assigned in MEPS. The model is estimated on a sample within 12 months above and below the age 228 months threshold. The controls used in this model include year indicators for the years 1996 to 2009, and the region indicators for Northeast, West, Midwest, and South regions.

Table 3: Reduced Form Estimates

	Age >228 months (α_1) (1)	SE (2)
Payment Variables:		
Total Payment From All Sources ($)	0.899	[3.462]
Total Payment from Private Insurance & Medicaid ($)	-7.614***	[2.148]
Payment by Sources:		
Out-of-Pocket ($)	5.771***	[2.018]
Private Insurance ($)	-9.986***	[2.325]
Medicaid ($)	2.474	[2.150]
Others ($)	2.640	[1.894]
Outcome Variables - Treatment Decisions:		
Any Medicine Prescribed	-0.036	[0.029]
Lab Tests	-0.039	[0.035]
Other Diag Test/Exam	-0.045	[0.036]
Actual Time Spent (1996-2000)	-0.413	[2.058]
Outcome Variables - Patients' Perception:		
Enough Time	-0.079**	[0.031]
Listen	-0.105***	[0.028]
Respect	-0.091**	[0.034]
Year Controls	Yes	
Region Controls	Yes	
Condition Control	Yes	
Observations	7,912	
Weighted	Yes	
Bandwidth	12 Months	

Notes. The standard errors are clustered at the age level, measured in months. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The model is estimated on a sample within 12 months above and below the age 228-month threshold. The control variables used in these regression models include year indicator variables for the years 1996 to 2009, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 4: Impact of the Change in Payments on the Actual and Perceived Behaviors of Medical Care Providers

	Outcome Variables Providers' Treatment Decisions:			Outcome Variables Patients' Perception:		
$(\frac{\alpha_1^{(outcome)}}{\alpha_1^{(treatment)}} \times \ \$10)$	Any Medicine Prescribed (1)	Lab Tests (2)	Other Diag Test/Exam (3)	Enough Time (4)	Listen (5)	Respect (6)
Payment Variables:						
Total Payment - All Sources ($)	-0.4004	-0.4338	-0.5006	-0.8788	-1.1680	-1.0122
	(1.5755)	(1.7015)	(1.9544)	(3.3994)	(4.5093)	(3.9114)
Total Payment - Private Ins & Medicaid ($)				0.1038**	0.1379***	0.1195**
				(0.0501)	(0.0535)	(0.0560)
Payment by Sources:						
Out-of-Pocket ($)				-0.1369**	-0.1819**	-0.1577**
				(0.0720)	(0.0800)	(0.0807)
Private Insurance ($)				0.0791**	0.1051***	0.0911**
				(0.0361)	(0.0372)	(0.0401)
Medicaid ($)				-0.3193	-0.4244	-0.3678
				(0.3045)	(0.3858)	(0.3479)
Others ($)				-0.2992	-0.3977	-0.3447
				(0.2447)	(0.3044)	(0.2788)
Year Controls	Yes					
Region Controls	Yes					
Condition Control	Yes					
Observations	7912					
Weighted	Yes					
Bandwidth	12 Months					

Notes. The standard errors are reported in brackets below the estimated coefficients. These standard errors are clustered at the age level, measured in months. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The effect to the change in payments on actual and perceived behaviors are calculated as Wald estimators. That is, the estimated outcome variables are divided by the estimated treatment variable. The standard errors for those Wald estimates are calculated using propagation of error formulas. The model is estimated on a sample within 12 months above and below the age 228 month threshold. The controls used in this model include year indicators for the years 1996 to 2009, and the region indicators for Northeast, West, Midwest, and South regions.

Table 5: Robustness Checks - Bandwidth Sensitivity

	Age >228 months		Age >228 months			Age >228 months
	(1)	(2)	(3)	(4)	(5)	(6)
Payment Variables:						
Total Payment From All Sources ($)	0.899	[3.462]	-2.165	[3.269]	1.327	[3.172]
Total Payment from Private Insurance & Medicaid ($)	-7.614***	[2.148]	-9.052***	[2.189]	-7.046***	[2.192]
Payment by Sources:						
Out-of-Pocket ($)	5.771***	[2.018]	4.917**	[1.886]	5.366***	[1.508]
Private Insurance ($)	-9.986***	[2.325]	-10.255***	[2.554]	-10.366***	[2.242]
Medicaid ($)	2.474	[2.150]	1.205	[2.441]	3.361	[1.983]
Others ($)	2.640	[1.894]	1.969	[2.060]	2.966*	[1.679]
Outcome Variables - Treatment Decisions:						
Any Medicine Prescribed	-0.036	[0.029]	0.016	[0.033]	-0.054*	[0.028]
Lab Tests	-0.039	[0.035]	-0.047	[0.041]	-0.036	[0.030]
Other Diag Test/Exam	-0.045	[0.036]	-0.06	[0.036]	-0.033	[0.033]
Outcome Variables - Patients' Perception:						
Enough Time	-0.079**	[0.031]	-0.063*	[0.031]	-0.080***	[0.027]
Listen	-0.105***	[0.028]	-0.090***	[0.030]	-0.110***	[0.025]
Respect	-0.091**	[0.034]	-0.089**	[0.034]	-0.089***	[0.028]
Year Controls	Yes		Yes		Yes	
Region Controls	Yes		Yes		Yes	
Condition Control	Yes		Yes		Yes	
Observations	7912		6323		8553	
Weighted	Yes		Yes		Yes	
Bandwidth	12 Months		9 Months		15 Months	
Outliers Dropped - Total payments	>$300		>$300		>$300	

Notes. The standard errors are reported in brackets next to the estimated coefficients. These standard errors are clustered at the age level, measured in months. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The model is estimated on a sample within 12 months above and below the age 228 months threshold. The control variables used in these regression models include year indicator variables for the years 1996 to 2009, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economics status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data is weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 6: Robustness Checks - Outlier Sensitivity

	Approx. 95th Percentile Age >228 months		Approx. 85th Percentile Age >228 months			Approx. 90th Percentile Age >228 months
	(1)	(2)	(3)	(4)	(5)	(6)
Payment Variables:						
Total Payment From All Sources ($)	0.899	[3.462]	0.661	[1.848]	0.691	[1.733]
Total Payment from Private Insurance & Medicaid ($)	-7.614***	[2.148]	-3.378**	[1.544]	-6.499**	[2.615]
Payment by Sources:						
Out-of-Pocket ($)	5.771***	[2.018]	4.087***	[1.177]	4.693***	[1.498]
Private Insurance ($)	-9.986***	[2.325]	-4.747**	[2.265]	-8.119**	[3.036]
Medicaid ($)	2.474	[2.150]	1.451	[1.641]	1.729	[2.053]
Others ($)	2.640	[1.894]	-0.131	[1.107]	2.389	[1.449]
Outcome Variables - Providers' Behaviors:						
Any Medicine Prescribed	-0.036	[0.029]	-0.042	[0.033]	-0.044	[0.031]
Lab Tests	-0.039	[0.035]	-0.045	[0.035]	-0.032	[0.033]
Other Diag Test/Exam	-0.045	[0.036]	-0.03	[0.040]	-0.034	[0.037]
Outcome Variables - Patients' Perception:						
Enough Time	-0.079**	[0.031]	-0.070*	[0.040]	-0.070*	[0.034]
Listen	-0.105***	[0.028]	-0.105***	[0.029]	-0.097***	[0.027]
Respect	-0.091**	[0.034]	-0.087**	[0.041]	-0.087**	[0.035]
Year Controls	Yes		Yes		Yes	
Region Controls	Yes		Yes		Yes	
Condition Control	Yes		Yes		Yes	
Observations	7912		6291		7578	
Weighted	Yes		Yes		Yes	
Bandwidth	12 Months		12 Months		12 Months	
Outliers Dropped - Total payments	>$300		>$100		>$200	

Notes. The standard errors are clustered at the age level, measured in months. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The model is estimated on a sample within 12 months above and below the age 228 months threshold. The control variables used in these regression models include year indicator variables for the years 1996 to 2009, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economics statsus, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data is weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

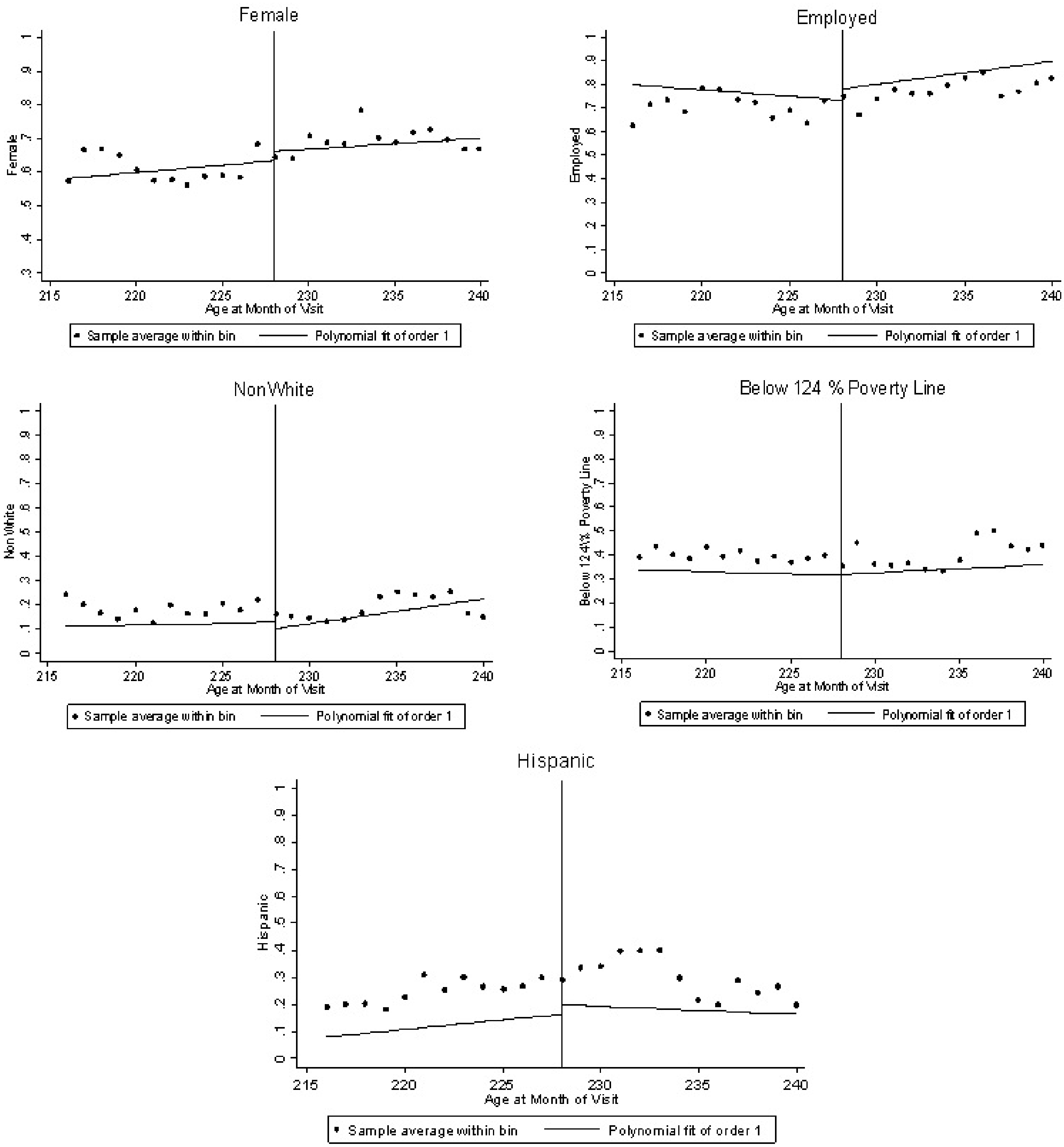

Figure 1: Covariates around 228 months

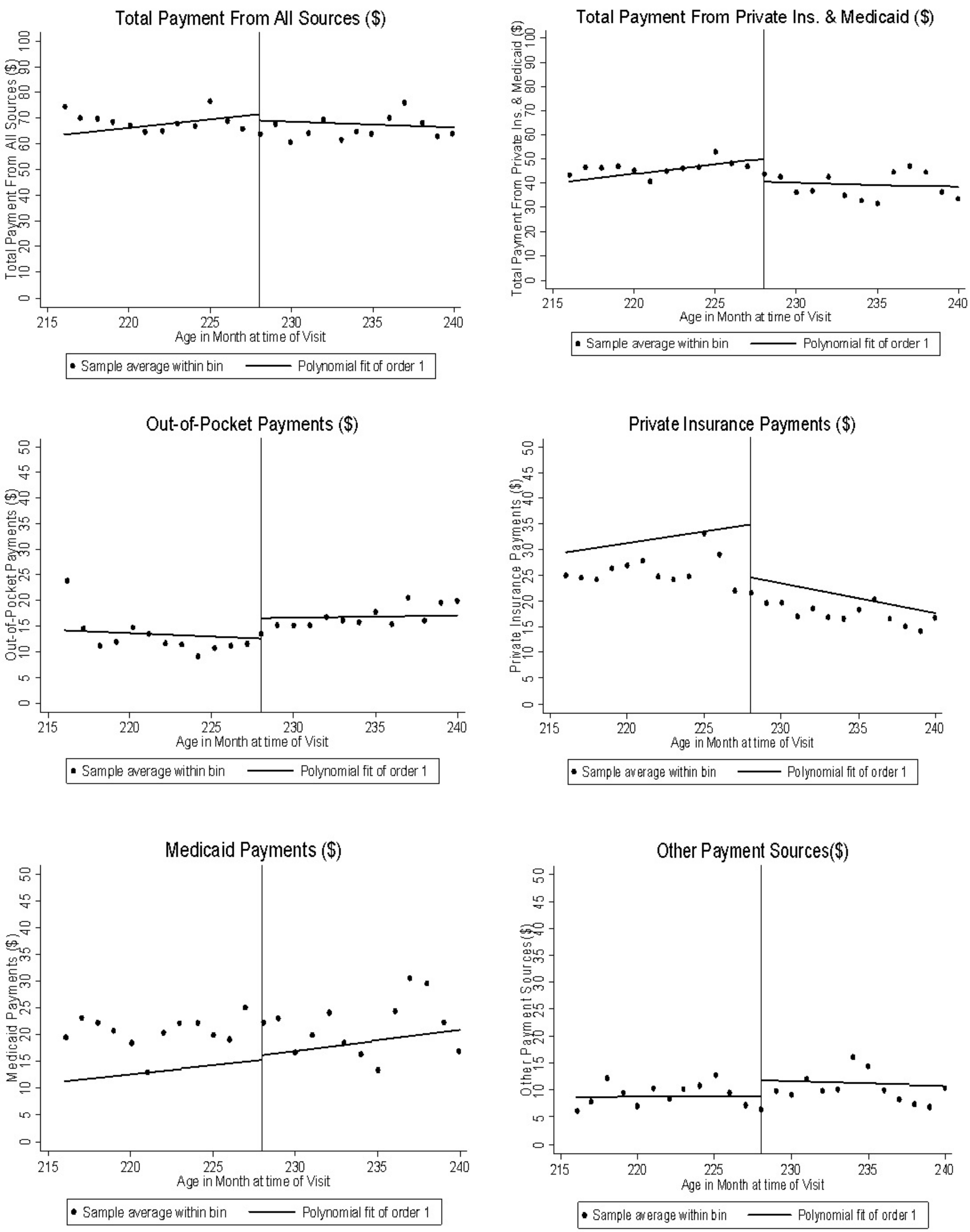

Figure 2: Payments around 228 months

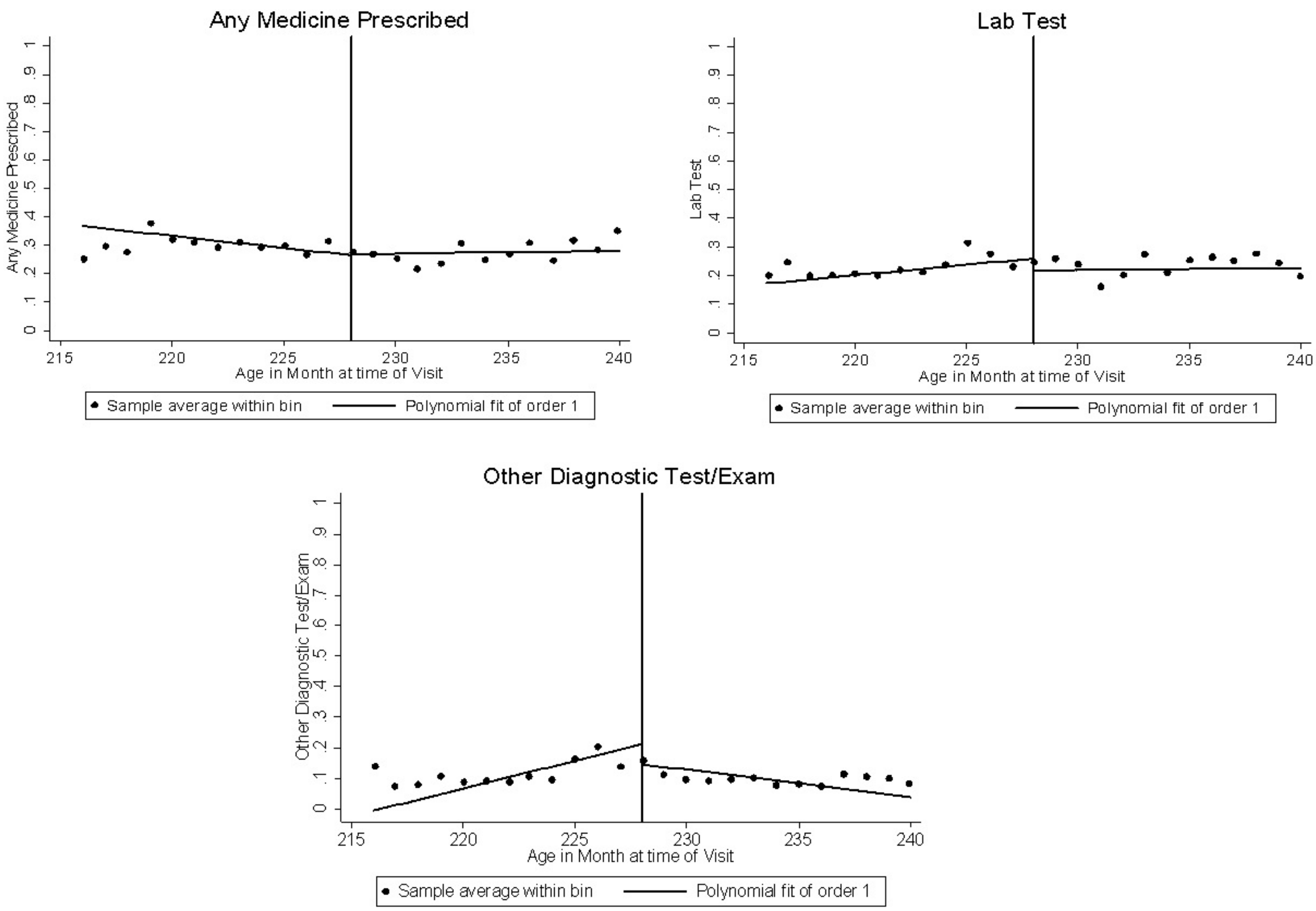

Figure 3: Actual Change in the Providers' Treatment Decisions around 228 months

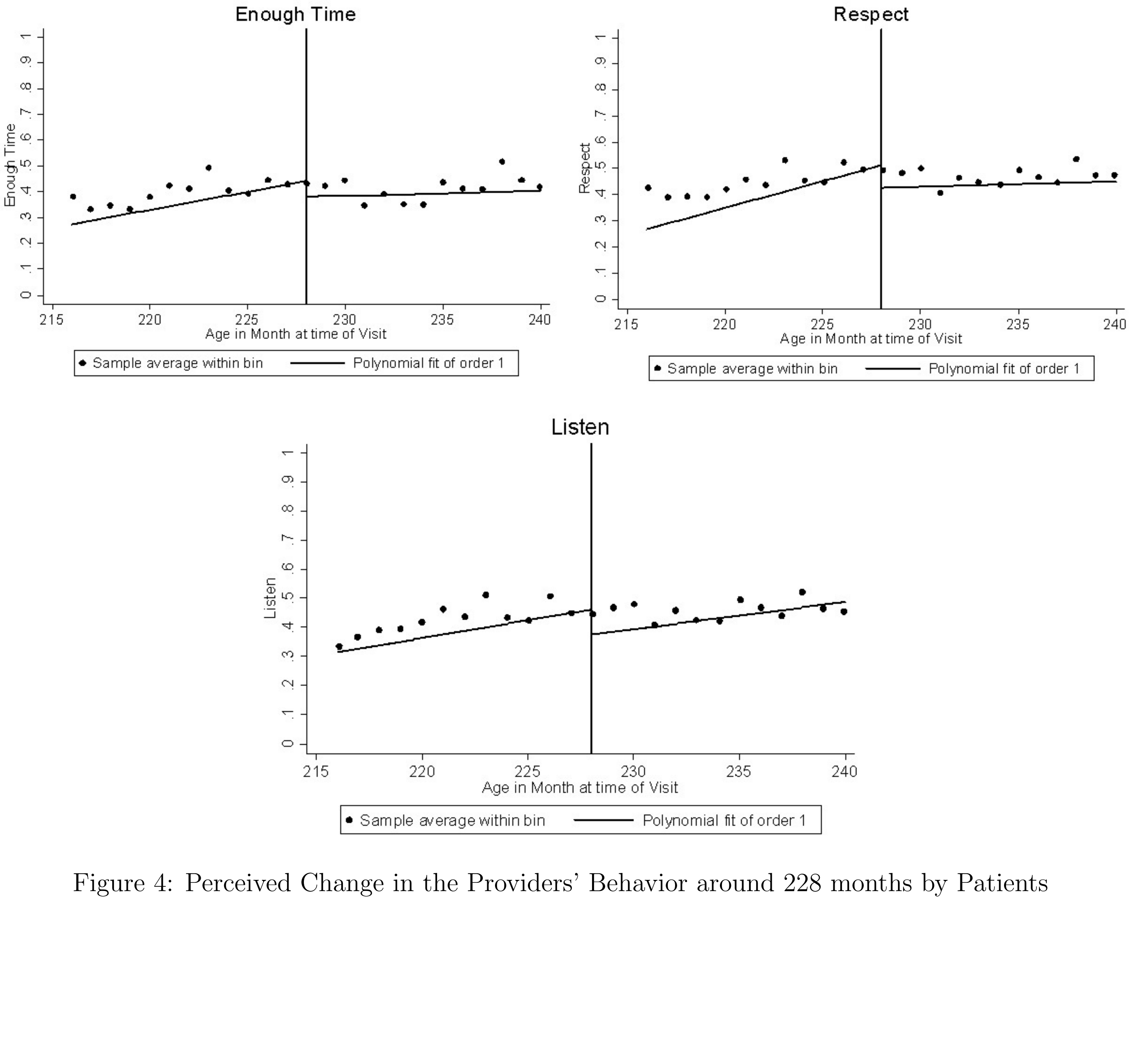

Figure 4: Perceived Change in the Providers' Behavior around 228 months by Patients

3 Chapter 2: The Impact of Regional Antimicrobial Use on Individual Antimicrobial Use, on Individual Health Outcomes, and on Regional Antimicrobial Resistance

3.1 Introduction

3.1.1 Antimicrobials

Antimicrobial is a general term that refers to a group of drugs that includes antibiotics, antifungals, antiprotozoals, and antivirals (Shiel, 2018). Antimicrobials are used to treat microbial infections. These medications kill or suppress the growth of harmful microorganisms such as bacteria, viruses, or fungi (U.S.EPA, 2017). Antimicrobial resistance (AMR) occurs when microorganisms such as bacteria, viruses, fungi and parasites are incurable with any known antimicrobial medication.

The CDC published an article which stated that any use of antimicrobial agents enhances the likelihood of resistance (Mcgowan Jr, 2001; CDC, 2017). When one microbe learns to be resistant to an antimicrobial, it is able to transfer that resistant gene to other microbes, even across species. Additionally, resistant microorganisms pass readily among people in communities (Johnson et al., 2009; Jain, 2010; Kesselheim and Outterson, 2011). Infection with a resistant organism has been associated with increased morbidity and mortality as well as increased hospital cost (Sydnor and Perl, 2011).

This paper suggests that as the issue of antimicrobial resistance and its impact on a person's quality of life continues to increase in importance (WHO, 2018), it is worth taking into account the regional differences in the antimicrobial prescription behavior and resistance levels as it can speak to the public health issue of antimicrobial resistance. To this effect, one of the questions addressed in this paper asks if living in a certain region affects the level of the antimicrobial prescription an individual receives for any given condition. Furthermore, this paper investigates if the regional level of antimicrobial usage affects the individuals' utilization of health care. The impact of regional levels of antimicrobial use on the antimicrobial resistance rates in those regions is also examined in this paper.

Although antimicrobial resistance can occur naturally, the primary force driving its evolution is the over-consumption and inappropriate use of medicines. Inappropriate use refers to the utilization of antimicrobials for infections they have no power to cure (WHO, 2017). Additionally, using antimicrobials - either properly or improperly - increases the propagation of resistance to the medications as the microbes that encounter these antimicrobials but are not affected by them can develop a resistance to the drug and then pass on that developed resistance gene onto other microbes including those that previously were not resistant to the antimicrobial medication (Michael et al., 2014). Moderating individuals' use of antimicrobials is therefore of extreme importance as AMR continues to grow as one of the biggest threats to good health in the world today, where a growing number of infections – such as pneumonia, tuberculosis, gonorrhoea, and salmonellosis – are becoming harder to treat as the antimicrobials used to treat them become less effective (WHO, 2018).

3.1.2 Literature Review

The consumption of antimicrobials as a treatment regimen is generally recognized as the primary driver of resistance patterns and that this is especially true when there is over-use and misuse of the antimicrobial medication (Austin et al., 1999; Granizo et al., 2000; Goossens et al., 2005; Sun et al., 2012). There is a large literature on factors contributing to the social over-consumption of antimicrobials (McDonnell, 2008; Bauchner et al., 1999; Macfarlane et al., 1997; Anomaly, 2010), including the prescription behavior of providers and the patients failure to adhere to recommended consumption guidelines. Along the lines of antimicrobial use and resistance, there is a breadth of research on the consumption of antibiotics as a treatment regimen. It is generally recognized as the primary driver of resistance patterns. This implies that as the number of individuals who use antimicrobials increase, the likelihood of misuse and thus resistance also increases. (Austin et al., 1999; Granizo et al., 2000; Goossens et al., 2005; Sun et al., 2012)

The correlation between the resistance to antimicrobials and health outcomes has been investigated. Multi-drug resistant bacteria are considered a serious public health concern because they put patients at risk for serious illness (and possibly death), they also place increased demand on already strained health care resources (Carmeli et al., 2002). Additionally, the literature shows that patients are not fully aware of the important consequences of antimicrobial use in the development of resistance (Eng et al., 2003; Belongia et al., 2002). However, there is a lack of empirical research on the differential impact of these relevant research areas in the various regions of the United States of America. This paper fills that gap by providing empirical research on the impact of living in certain regions on an individual's antimicrobial use, potential antimicrobial resistance, as well as the impact of regional use of antimicrobial medication on the individual's interaction with the health care industry.

This paper contributes to the literature on externality of regional antimicrobial use in the following respects. First, the impact of regional use of antimicrobials on individual use of antimicrobials, and their interaction with the health care system is studied directly,. The research by Johnson et al. (2009); Kesselheim and Outterson (2011); Johnson et al. (2009); Jain (2010) shows that resistant microorganisms pass readily among people in communities, and even more readily among the sickest people in hospitals or other health care delivery institutions. This is where this paper steps in to fill the need for empirical evidence on the influence of the patient's society, as defined as a region, on their use of antimicrobials. Second, this paper leverages the lagged yearly average of regional antimicrobial use to properly identify and quantify the impact of various levels of antimicrobial use in the regions of concern. This methodology contributes to the current literature, as despite it's significance identification properties, it has not been implemented. Third, it combines the study of regional use with regional resistance using two consequential data sources.

The rest of the paper is organized as follows; section 2 discusses the dataset and how the analysis sample is built. Section 3 presents the empirical framework and discusses the identification strategy. Section 4 discusses the results and section 5 is the discussion and summary section of this paper. The tables and firgures for this paper are at the displayed end, after the references.

3.2 Data

3.2.1 Data Description

The two sources of data used in this paper are the Medical Expenditure Panel Survey (MEPS) dataset, and the National Antimicrobial Resistance Monitoring System (NARMS) dataset. The primary source of data is MEPS, with NARMS providing secondary data on the regional levels of antimicrobial resistance over the years.

MEPS, fielded by the Agency for Health care Research and Quality (AHRQ), is a set of large-scale nationally representative surveys of families and individuals, their medical providers, and employers across the United States (AHRQ, 2009, 2018, 2008a; Cohen et al., 2009). It is the most complete source of data on the cost and use of health care including the specific health services that Americans use, how frequently they use them, the cost of these services, and how they are paid for (AHRQ, 2009).

The MEPS data has a series of public use event files from the Medical Expenditure Panel Survey Household Component (MEPS HC) and Medical Provider Component (MPC). One of such event files is the Prescribed Medicines File which provides detailed information on household-reported prescribed medicines for a nationally representative sample of the civilian non-institutionalized population of the United States and can be used to make estimates of prescribed medicine utilization and expenditures for each calendar year (AHRQ, 2014). Each record on this event file represents a unique prescribed medicine event; that is, a prescribed medicine reported as being purchased or otherwise obtained by the household respondent, and includes the following: an identifier for each unique prescribed medicine; detailed characteristics associated with the event (e.g., national drug code (NDC), medicine name, etc.); selected Multum Lexicon variables [9] conditions, if any, associated with the medicine; the date on which the person first used the medicine; total expenditure and sources of payments; and a full-year person level weight (AHRQ, 2014).

NARMS is a collaboration among state and local public health departments, CDC, the U.S. Food and Drug Administration (FDA), and the U.S. Department of Agriculture (USDA). NARMS is a national public health surveillance system that tracks changes in the antimicrobial susceptibility of certain enteric (intestinal) bacteria found in ill people (CDC), retail meats (FDA), and food animals (USDA) in the United States. Through NARMS, experts track and study changes in antibiotic resistance among several bacteria (CDC, 2019a). The antibiotic resistance data from bacteria isolated from humans is available for download on NARMS (CDC, 2019b). This is the secondary source of data used in this paper, as it contains antimicrobial resistance level data for different regions in the USA, beginning in the year of 1996.

3.2.2 Analysis Sample

Primarily, this research uses prescribed medicine event at the aggregated to the individual level data merged with household/individual level data from the consolidated household component file for the analysis from the MEPS data source.

[9]Multum's therapeutic classification of drugs according to the therapeutic purposes of the drugs. It is administrated by the Cerner Multum drug, herbal and nutraceutical database, a leading industry resource designed to assist with safe medication use efforts (Cerner, 2019; MEPS, 2013).

Additionally, yearly regional averages of antimicrobial resistance from NARMS were amalgamated to the MEPS prescription level merged data file.

Although the publicly available MEPS data spans 1996 to 2015, the sample used in this paper is limited to the years 2002 through 2012. The reason 2002 shows up as the first year in the sample is because the important piece of information necessary for this analysis, regarding the type of prescription being used in each prescription event, (specifically, the Multum Therapeutic Class #1 (TC1)), is not reported in the dataset until 2002. The sample ends at 2012 because the variable in the dataset that shows the 3 digit International Classification of Diseases, Ninth Revision (ICD-9-CM) condition code stops being reported in 2012.[10] In an effort to protect the identity of the respondents, the condition codes were grouped up to the 3 digit ICD-9-CM condition codes. The usefulness of the conditions information is not affected by this action (AHRQ, 2008b). There are 649 ICD-9-CM condition codes in the sample.[11]

There are four census-based regions provided by MEPS included in the sample, denoting the region where an individual lived when the prescription event occurred. The regions are Northeast, Midwest, South, and West. The states in the U.S. are distributed to each of the four regions according to the method in which the United

[10]The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) is based on the World Health Organization's Ninth Revision, International Classification of Diseases (ICD-9). ICD-9-CM is the official system of assigning codes to diagnoses and procedures associated with hospital utilization in the United States (**?**).

[11]Example of an ICD9 code classification is 460, which represents conditions classified as Acute nasopharyngitis (common cold).

States Census Bureau defines four statistical regions (Bureau, 2018).

One of the main variables used for analysis in this research is the yearly regional average of the proportion of prescriptions that have the Multum Therapeutic class #1 antimicrobial designation (TC1 = 1) for each ICD-9-CM condition code. In order to properly estimate the effect of this regional antimicrobial use, this paper instruments the yearly averages with the regional yearly averages that have been lagged by one time period. The observations with missing lagged values are not included in the analysis. Observations with missing information for the main variables in the estimated empirical equation are not included in the analysis. Along with the yearly averages, this paper uses the monthly averages for all the years included in the sample as a robustness check of the main analysis done in the paper. This serves as a check of the instruments ensuring that the choice of yearly averages in the main results of the paper was not guided by its favorable estimated values and statistical significance. Observations without information on the month that the individual started taking the prescribed medication are excluded.

In MEPS, it is possible to distinguish doctor visits from non-physician visits. Non-physician visits are visits to chiropractors, midwives, nurses and nurse practitioners, optometrists, podiatrists, physician's assistants, physical therapists, occupational therapists, psychologists, social workers, technicians, and receptionists/clerks/secretaries (AHRQ, 2009). This is relevant for this analysis because the research is limited to physicians because it relates to the prescription of medication. The medical care provided on an outpatient basis, including diagnosis, observation, consultation, treatment, intervention, and rehabilitation services is labeled as Ambulatory care in

MEPS. This variable is used to measure the interaction with health care services in different regions over time.

The sample includes data from NARMS in order to perform the analysis of regional antimicrobial use on regional antimicrobial resistance. The NARMS dataset includes a variable that states the region in which the microbes were tested for their resistance to antimicrobials. Using the information on the region for each observation, the average proportion of the tested microbes that were resistant to the antimicrobial medication(s) was calculated for each region in the years that spanned 2002 through 2012. These regional averages were then merged to the MEPS sample using the region variable for each year.

The summary statistics of the variables used in this paper are shown in table 7. The sample size of the data used here is 214,021. However, the sample size of the regression analysis is 184,708 because it includes the lagged variable. Of the 214,021 individuals in the sample that received a prescription, there are 81,197 (37.94% of the sample) individuals who filled an antimicrobial prescription. The remaining 132,824 individuals filled prescriptions that were not antimicrobials. On average, the number of times an individual filled a unique antimicrobial prescription is 0.81 in any given year. The maximum number of occurrences in a year where an individual filled an antimicrobial prescription is 107. This antimicrobial usage differs across the regions. The region with the highest antimicrobial usage is the Midwest with an average of 0.87 occurrences per individual per year, and the region with the lowest usage is the West with an average of 0.75 occurrences. In the sample frame, the average rate of resistance to antimicrobials measured by the CDC is 38.77%. The resistance levels in the regions is interestingly highest in the Northeast, with a value of 43.75%, and lowest in the West with an average value of 36.93%.

There is an average of 6.6 visits to the physician's office by an individual in a year, with a maximum of 338 physician office visits in a year. The individual yearly average of visits to the outpatient department is 0.26 with a maximum of 174 visits. The emergency department has an average of 0.285 visits in a year by an individual, with a maximum of 22 visits in the sample. The instance of a hospital admittance without an overnight stay occurred on average, 0.004 times on average for an individual, with 8 as the maximum number of occurrence in the sample. The number of times an individual in the sample was admitted to the hospital and stayed overnight was an average of 0.136, where the maximum occurrence in the sample was 16 times for an individual.

In the sample, the average total expenditure on health care for any given individual is $4.979.31. The maximum amount spent in year on health care by an individual in the sample is $2,226,997. The demographic variables are indicator variables that equal one when the individual associated with a given prescription belongs to that demographic.

3.3 Empirical Framework

This paper researches the impact of regional antimicrobial use on individual use of antimicrobials, on individuals' use of with the health care industry, and on the regional levels of antimicrobial resistance. The econometric framework of this analysis is a two stage least squares (2SLS) model, where the instrumental variable is the one period lagged yearly regional average of antimicrobial use for any given condition. This instrument is for the yearly regional average of antimicrobial use for any given condition, the key dependent variable in the model. The instrument is valid as it meets the requirements of being a strong instrument for the current regional average, and of having a valid exclusion restriction. This validity is confirmed using the Sargen-Hansen test of over-identifying restrictions, where the joint null hypothesis is that the instruments are valid instruments, i.e., uncorrelated with the error term, and that the excluded instruments are correctly excluded from the estimated equation (Baum et al., 2018).

The main model of interest is:

$$Y_{irt} = \beta_0 + \beta_1 \mathrm{RegUse}_{rt} + \delta \mathrm{X}_i + \mathrm{T}_t + \mathrm{R}_r + \mathrm{ICD9}_{irt} + u_{irt} \tag{3}$$

The first stage of the 2SLS regression equation estimated is:

$$\mathrm{RegUse}_{rt} = \alpha_0 + \alpha_1 \mathrm{RegUse}_{rt-1} + \delta \mathrm{X}_i + \mathrm{T}_t + \mathrm{R}_r + \mathrm{ICD9}_{irt} + u_{rt} \tag{4}$$

where Y_{pirt} represents the various outcomes of interest from the reduced form equations for individual (i), in region (r), at time (t). The main dependent variable which is the first outcome of interest measures the total number of times an individual fills an antimicrobial prescription medication for any given condition in a year. Additionally, this paper measures the effectiveness of the change in regional antimicrobial use with six outcome variables, namely the total number of office-based physician visits, total number of outpatient dept physician visits, total number of emergency room visits, total number of overnight inpatient hospital stays, total number of zero-night inpatient hospital stays, and the total health care expenditure, that each individual made in a year.

RegUse_{rt} is the average yearly regional use of antimicrobials, in the current time period (t) for region (r). This is the main variable of interest with the coefficient β_1. RegUse_{rt-1} is the average yearly regional use of antimicrobials, lagged by one-year (t-1) for each region (r). This is the instrumental variable for the current regional average use. Although the grouping of the regions is relatively large, the analysis done here still applies. The use of antimicrobials by people in one region can significantly affect geographically and temporally distant people (Anomaly, 2010).

X_i is a vector of the individual's demographic variables in the sample. The demographic variables used in this analysis are: race (equals one if the patient is White and zero otherwise), gender (equals one if the individual is female, and zero otherwise), ethnicity (equals one if the patient is Hispanic and zero otherwise). Also includes: employment status (equals one if the patient is employed, either full-time or part-time employed and zero if unemployed), marital status (equals one if patient is married and zero otherwise[12]), insurance status (equals one if the individual has any type of insurance coverage at any point in the year), educated which refers to an individual who either has a high school diploma and higher, or is currently in school. Smoker (equals one if the individual was a smoker, and zero otherwise).

[12]The other categories that comprise of other than married, are Separated, Divorced, Widowed, and Never Married.

T_t represents the year fixed effects, where each year has a dichotomous variable included in the equation. This is to control for any possible impact on individual use of antimicrobials that is due to the year in which the event occurred.

R_r represents the fixed effects for each of the four regions in the dataset, where each region has a dichotomous variable included in the equation. This is to measure the differential impacts on the individuals resulting from being a given region vs another.

$ICD9_{irt}$ represents the conditions fixed effects in the sample. There are 649 of these ICD-9-CM condition codes which have been aggregated into nineteen clinically meaningful categories that group similar conditions (AHRQ, 2008b). These fixed effects control for any possible impact on individual use of antimicrobials that is due to the conditions for which the event occurred. This allows for the validity of the prescribed antimicrobials resulting from the conditions for which the individuals received the prescriptions.

All estimations of equation 9 and equation 4 are weighted using the final person weight, called PERWTF in the household component data of MEPS. The standard errors are clustered at the region-year level (Lee and Card, 2008). An example of such a cluster would be 2002_1 representing year 2002, in the Northeast region. There are 44 of these clusters in the sample.

3.4 Results

3.4.1 Lagged Regional Use on Current Regional Use of Antimicrobial Prescribed Medicine

The main variable of interest in this paper is the regional use of antimicrobials in the current time period. In order to properly identify it's impact, this paper used the one-year lagged regional average use of antimicrobials to instrument the current regional antimicrobial usage. This first stage analysis shows that there is a strong positive impact of the lagged yearly average of regional use of antimicrobials on the current use of antimicrobials, by a magnitude of 0.092. This is a relative increase of 11.36% given that the average number of times antimicrobial prescriptions are filled in a given year is 0.81. Therefore if the level of antimicrobials prescriptions used in a region increases by one percentage point in the previous year, then the antimicrobial prescriptions used in a region would increase by 0.092 in the current year. The level of antimicrobial prescription use refers to the yearly average of the number of antimicrobial prescriptions filled by individuals in a given region.

The results here in table 8 also includes the estimates for the current regional use of antimicrobials with a change in the lag period from a one-year lag to a two-year lag, and a three-year lag period. The sign and significance of these estimates are very similar. The magnitude of the effect of the lagged period average on the current average first increases then decreases as the lag period increases. This information is significant as various world health organizations continue to work to curtail the use of antimicrobials, and as the effect of their implemented methodologies are measured.

As a robustness check of the aggregation level of the regional uses to the yearly level, this paper uses the regional monthly averages for all the years. This result is shown in table 12. The statistical significance and estimated sign are consistent when the regional use is aggregated at the month level. There is a significant and positive impact by the magnitude of 0.082 units of a one-month lagged regional average, on the current level of regional use of antimicrobials. This impact decreases as the number of lagged months increase, it does however remain statistically significant.

3.4.2 Regional Use on Individuals' Use of Antimicrobial Prescribed Medicine

This result here are shown in table 9. It shows the impact of regional use of antimicrobials on an individual's use of antimicrobial in a given year. There is a significant impact with a magnitude of 0.067, of the level of use of antimicrobials in a region on the number of times an individual fills a prescription in a year for any given condition. This is a 8.71% increase given the average of 0.81 occurrences in a year. This implies that in areas where the level of antimicrobial use is low would thus lead to a low level of antimicrobial use by an individual.

This result varies among the four regions. Compared to the Western region, there is a higher impact on individual use of the regional use from the Midwestern and Southern regions by 0.0015 and 0.008 respectively. There is, however, no statistically significant difference in the impact of regional use on individual use between the Western and Northeastern regions.

It is important to note here that this result does not directly account for the validity of the antimicrobial prescription, but instead looks directly at the use of the antimicrobials regardless of its appropriateness. This is relevant given the increasing evidence that any exposure to antimicrobial medication increases the likelihood of developing a resistance (Michael et al., 2014)

3.4.3 Regional Use on the Individuals' Use of the Health Care System

There are six measures of an individual's use of the health care system measured here. These variables are total number of office-based physician visits; total number of outpatient department physician visits; total number of emergency department visits; total number of zero-night hospital stays; total number of hospital discharges; and the total health expenditure for the year associated with each individual represented in the prescription sample. Here the results, as seen in table 10, suggest that there is no significant impact of the regional level use of antimicrobials on any of the measures of a resident's interaction with the health care system.

This is relevant because there are a number of studies that suggest that the use of antimicrobials in the proper treatment of microbes will positively impact the health of the members of the region as it prevents the spread of these organisms. Thus reducing the need for health care by those who did not receive the microbes - because the original carrier killed the microbes in their body. This is the positive outcome and externality of antimicrobial use. However, there is the negative impact from the use of antimicrobials, namely the increased likelihood of the microbes in the individual developing resistance to the antimicrobial prescriptions, and further the spread of the antimicrobial-resistant microbes among individuals in the regions. Thus increase the use of health care and health care expenditure for the individuals.

Given that the results show that there is neither positive nor negative significant impact of the regional use of antimicrobials on the six measures of the intensity of use of various health care services available to the individuals, it can be argued that either these negative and positive impacts are cancelled out by each other. That is, the benefit of taking antimicrobials to kill the microbes in an individual and thus prevent the spread of the microbes is not out-weighted by the negative impact of taking antimicrobials on the increased likelihood of resistance.

The medical literature suggests that as resistance levels occur the expense related to curing a microbial infection increases significantly. Therefore, the lack of a significant change in the total health expenditure does signal that there is some - at the very least - non-negative outcome related with the use of antimicrobials and resistance. It is possible to ascribe this lack of significance to the overall decrease in use of antimicrobials across the country.

3.4.4 Regional Use of Antimicrobial Medications on Regional Antimicrobial Resistance Levels

Given the volume of literature that indicates that the use - especially improper use - of antimicrobials leads to antimicrobial resistance, it came as a bitter comfort that this research paper also finds that there exists a positive and significant impact of the use of antimicrobials on the levels of AMR in the regions to the magnitude of 0.087. That is to say that an increase in the regional use of antimicrobials by one percentage point will lead to a 8.7 percentage point increase in occurrence of resistant microbes. This is a 22.38% increase given the overall resistance average of 38.77%. It should be noted that the resistance levels are measured by the CDC as the proportion of assessed microbes in each region which showed resistance to any antimicrobial medication that would have otherwise eradicated the microbe.

When investigated separately, the results show that this significant positive impact of use on resistance is consistent for all four regions. However, there are differences in the magnitude across the various regions. The Northeast is ranked highest - the relatively worst position - with a magnitude of 14.1 percentage points. It is followed closely, by South in second place, with a magnitude of 11.6 percentage points. In third place out of the four regional groupings in the sample is Midwest with a magnitude of 5.8 percentage points and in fourth place (the relatively best option) is the West with a magnitude of 3.1 percentage points. The West is the relatively best option because it is the region where the impact of regional use of antimicrobial prescriptions least affects their regional resistance level. It is worth noting that the Western region has the lowest rate of antimicrobial resistance occurrence, given the NARMS data.

Although these regional groupings are relatively large, they do show an interesting view of the relationship between aggregate level of antimicrobial use and resistance, and suggest that more granular regional studies of these relationships would be beneficial to public health organizations as the effort to combat AMR continues.

3.5 Discussion and Summary

The world urgently needs to change the way it prescribes and uses antimicrobials. Even if new medicines are developed, without behaviour change, antimicrobial resistance will remain a major threat. Looking at the use of antimicrobials in the United States over time in figure 5, there is a decrease in general from the year 2002 until the sample ends in the year 2012. However, doing this same analysis for the different regions, it is clear that the magnitude of the decrease is not consistent for all the regions where there is a slightly larger decrease in the Southern region overall than in all the other regions, as seen in figure 6.

There have been large scale modifications implemented to reduce the occurrence of AMR which is good. There however is evidence that shows that more work still needs to be done. Leading academic groups, public health organizations, and governments have recently become more vocal about the problem of drug-resistant infections. The Alliance for the Prudent Use of Antibiotics has been focused for many years on resistance stemming from the misuse of antibiotics (Levy, 2000). Sun et al. (2012) find restrictions imposed at the hospital level that are unlikely to be effective unless coordinated with campaigns to reduce unnecessary antibiotic use at the community level. This is especially true as resistance occurrence is happening faster than newer versions of antimicrobials are being discovered.

In summary, this paper investigates the impact of the regional use of antimicrobials on three main areas, namely: the yearly level antimicrobial use by an individual; an individual's use of health care; and the level of antimicrobial resistance in the four regions as defined as Midwest, Northeast, South, and West. The results of the investigation show that firstly, there is a direct and significant relationship between the regional level of antimicrobial use and a persons' level of antimicrobial use in a year to treat any given condition. This implies the presence of a negative externality on individuals in the various regions, especially in the regions with relatively high antimicrobial use. Secondly, the regional use of antimicrobials does not lead to a positive improvement - that is, a reduction - of the individuals' use of health care. This indicates that the extent of antimicrobial use in the various regions is improper. Lastly, the results of the investigation show that the use of antimicrobials in various regions leads to a significant increase in antimicrobial resistance levels in the those regions. The magnitude of the increase differs across the various regions.

Therefore, given that the consumption of antimicrobials as a treatment regimen is generally recognized as the primary driver of resistance patterns and that this is especially true when there is over-use and misuse of the antimicrobial medication, this work strongly recommends that as the public health organization continue to create guidelines to foster the reduction of antimicrobial resistance, they consider the various region in which the guidelines and policies will be implemented as the use and resistance levels in these regions vary significantly.

With respect to the particular drivers of the significant positive impact of regional use of antimicrobials of individual use, it would be interesting to investigate further in future research. The determination of how much of that regional impact is due to the patients peer effects of living in a particular region given the way the other residents use antimicrobials especially in their interactions with the different providers. The other part of that investigation would be to see if there is any pressure from the patients on the physician to prescribe antimicrobials. The patients view the visits as valuable only when there is such a prescription occurrence. It would also go further to investigate if the physicians are responsive to these pressures in order to appease their clientele - the patients.

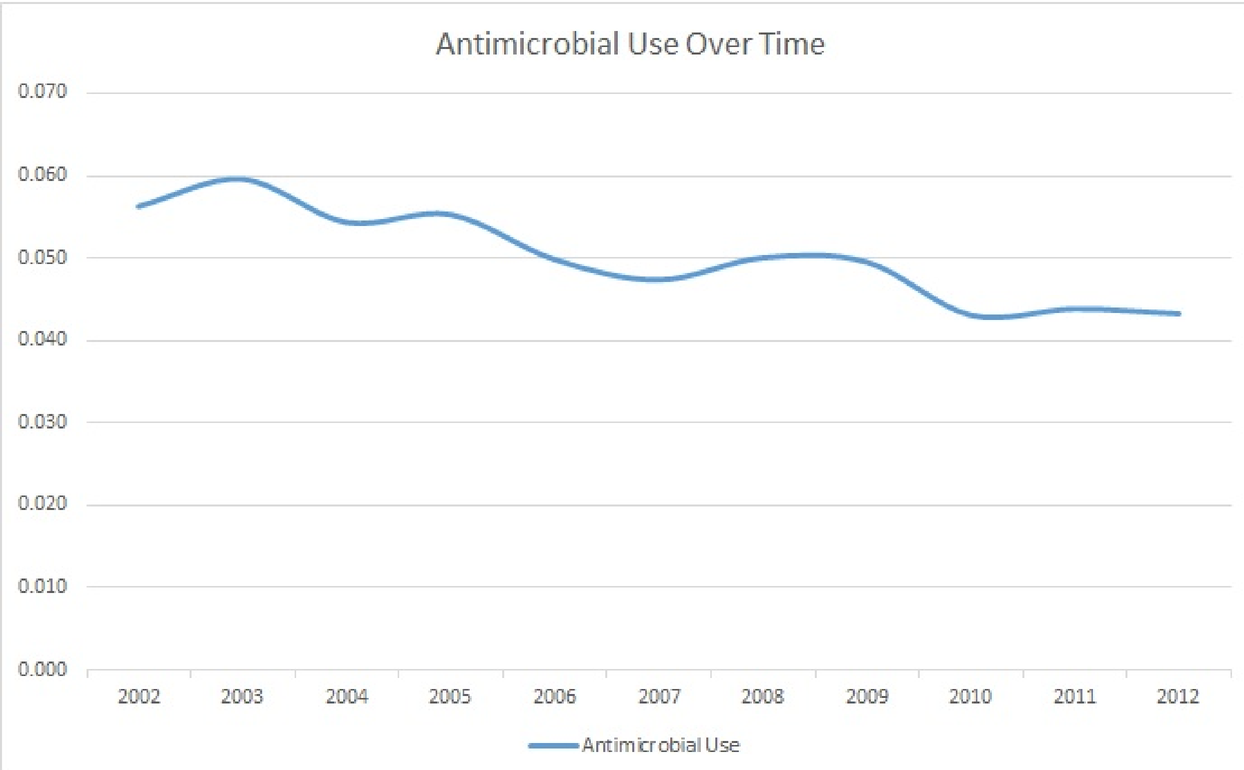

Figure 5: Antimicrobial Use Over Time

Table 7: Sample Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Level of Antimicrobial Prescription Use				
Overall Level of Antimicrobial Prescription Use	0.81	2.17	0	107
Midwest Level of Antimicrobial Prescription Use	0.87	2.05	0	72
Northeast Level of Antimicrobial Prescription Use	0.76	2.18	0	89
South Level of Antimicrobial Prescription Use	0.84	2.29	0	107
West Level of Antimicrobial Prescription Use	0.75	2.06	0	85
Antimicrobial Resistance				
Overall Resistance Level	38.77%	4.72%	29.88%	56.61%
Midwest Resistance Level	40.52%	4.66%	29.88%	45.53%
Northeast Resistance Level	43.75%	7.26%	31.08%	56.61%
South Resistance Level	36.99%	2.27%	32.53%	40.42%
West Resistance Level	36.93%	1.96%	34.25%	41.29%
Health Care Use Variables				
Number of Office-Based Physician Visits	6.643	11.099	0	338
Number of Outpatient Dept Physician Visits	0.263	1.883	0	174
Number of Emergency Dept. Visits	0.285	0.717	0	22
Number of Zero-Night Hopsital Stays	0.004	0.078	0	8
Number of Hopsital Discharges	0.136	0.480	0	16
Total Medical Expenditure	4979.31	13790.53	0	2,226,997
Demographic Variables				
Smoker	0.1340	0.3407	0	1
Employed	0.4845	0.4998	0	1
Educated	0.7797	0.4145	0	1
Never Married	0.1985	0.3988	0	1
Separated	0.1603	0.3669	0	1
Married	0.0878	0.2830	0	1
Divorced	0.2053	0.4039	0	1
Widowed	0.0521	0.2223	0	1
Female	0.5697	0.4951	0	1
Insured	0.9050	0.2932	0	1
Black	0.1719	0.3773	0	1
White	0.7544	0.4305	0	1
Other Race	0.0738	0.2614	0	1
Hispanic	0.2148	0.4107	0	1
Age	40.3968	23.6970	0	85

Notes: The number of observations for the entire sample is 214,021, 45,508 for the Midwest region, 33,190 for the Northeast region, 83,772 for the South region, and 51,551 for the West region. The percentage values are the proportion of the sample for which the reported variable is true.

Table 8: Lagged Regional Use on Current Regional Use of Antimicrobial Prescribed Medicine

	(1)	(2)	(3)
One-Year Lagged Regional Use of Antimicrobials	0.092***		
	[0.003]		
Two-Year Lagged Regional Use of Antimicrobials		0.178***	
		[0.002]	
Three-Year Lagged Regional Use of Antimicrobials			0.026***
			[0.003]
Observations	184,708	164,992	145,743
SE	Cluster	Cluster	Cluster
Cluster	Year_Region	Year_Region	Year_Region
Weighted	Yes	Yes	Yes
YearFE	Yes	Yes	Yes
RegionFE	Yes	Yes	Yes
ConditionsFE	Yes	Yes	Yes

Notes: The standard errors are clustered at the year, and regional level, where one cluster of 2002_1 indicates year 2002, in the Northeast region. There are 44 of these clusters. Clustered standard errors in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). The control variables used in these regression models include year indicator variables for the years 2002 to 2012, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 9: Regional Use on Individual Use of Antimicrobial Prescribed Medicine

IV = One-Year Lagged Regional Use	Current Regional Use
Individual Level Use of Antimicrobials	0.067**
	[0.033]
Regional Differences (Base Region is West)	
Northeast	-0.003
	[0.019]
Midwest	0.015***
	[0.0004]
South	0.008***
	[0.002]
Observations	184,708
SE	Cluster
Cluster	Year_Region
Regression Model	2SLS
Weighted	Yes
YearFE	Yes
RegionFE	Yes
ConditionsFE	Yes

Notes: The standard errors are clustered at the year and region level, where one cluster of 2002_1 indicates year 2002, in the Northeast region. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The control variables used in these regression models include year indicator variables for the years 2002 to 2012, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 10: Regional Use on the Individual's Interaction with the Health Care System

Health Care Outcomes	Current Regional Use
Number of Office-Based Physician Visits	0.061
	[0.365]
Number of Outpatient Dept Physician Visits	0.091
	[0.173]
Number of Emergency Dept. Visits	-0.012
	[0.077]
Number of Zero-Night Hopsital Stays	-0.002
	[0.009]
Number of Hopsital Discharges	0.04
	[0.065]
Total Medical Expenditure	-739.53
	[821.72]
Observations	184,708
SE	Cluster
Cluster	Year_Region
Regression Model	2SLS
Weighted	Yes
YearFE	Yes
RegionFE	Yes
ConditionsFE	Yes

Notes: The standard errors are clustered at the year and region level, where one cluster of 2002_1 indicates year 2002, in the Northeast region. Clustered standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The control variables used in these regression models include year indicator variables for the years 2002 to 2012, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 11: Regional Use of Antimicrobial Medications on Regional Antimicrobial Resistance Levels

	Regional Antimicrobial Resistance				
	(1)	(2)	(3)	(4)	(5)
Regional Use of Antimicrobial	0.087***	0.058***	0.141***	0.116***	0.031***
	[0.033]	[0.067]	[0.021]	[0.048]	[0.011]
Observations	44	11	11	11	11
Region	All	Midwest	Northeast	South	West
SE	Robust				
Regression Model	2SLS				
Instrument	One - Year Lagged Regional Average				
Weighted	Yes				
ConditionsFE	Yes				

Notes: The standard errors are heteroskedastic robust. Robust standard errors in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). The control variables used in these regression models includes year indicator variables for the years 2002 to 2012. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 12: Robustness Check - Lagged Regional Average

	(1)	(2)	(3)
One-Month Lagged Regional Use of Antimicrobials	0.082***		
	[0.009]		
Two-Month Lagged Regional Use of Antimicrobials		0.065***	
		[0.011]	
Three-Month Lagged Regional Use of Antimicrobials			0.029***
			[0.011]
Observations	184,708	164,992	145,743
SE	Cluster	Cluster	Cluster
Cluster	Year_Month_Region	Year_Month_Region	Year_Month_Region
Weighted	Yes	Yes	Yes
YearFE	Yes	Yes	Yes
RegionFE	Yes	Yes	Yes
ConditionsFE	Yes	Yes	Yes

Notes: The standard errors are clustered at the year, month, condition, and regional level, where one cluster of 2002_1_resp_1 indicates year 2002, month of January, respiratory conditions, in the Northeast region. Clustered standard errors in brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$). The control variables used in these regression models include year indicator variables for the years 2002 to 2012, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and employment status. The conditions addressed during each visit as categorized by ICD9 codes are also controlled for in the model. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

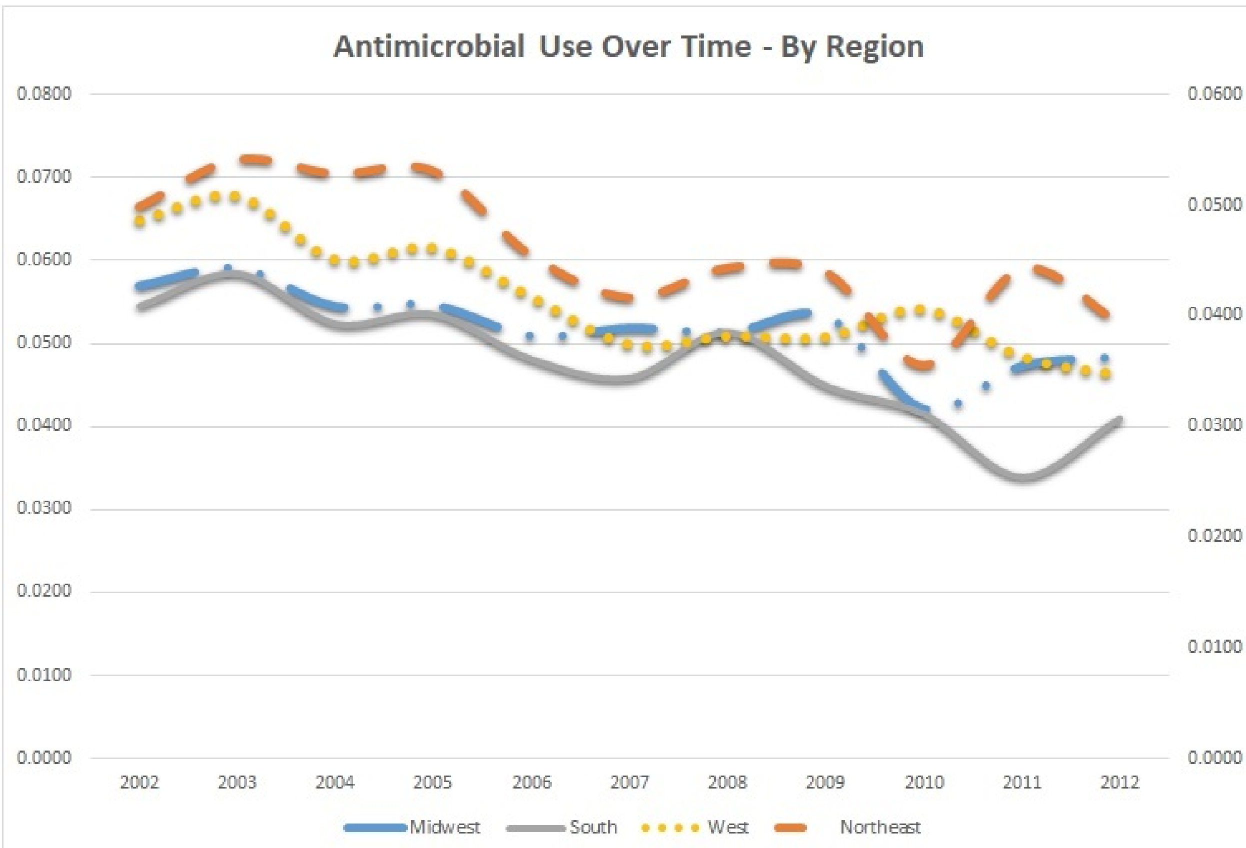

Figure 6: Antimicrobial Use Over Time - By Region

4 Chapter 3: Impact of the Price of Physician Visit on the Volume of Prescribed Medicine: A Focus on Antibiotics and the Common Cold

4.1 Introduction and Literature Review

There are many reasons why the need to control the dispensing and consumption of medication can arise; these reasons are mainly a social benefit to the individuals who would come to harm as result of the inappropriate consumption of the medications if they were not controlled. Many supporters of the need for controlling medications, including the FDA, cite the lack of awareness by said individuals of the potential harm to the health that could result from the misuse of the controlled medications. This potential harm is avoided by the incurring of the additional cost of visiting the doctor's office and receiving a prescription for the controlled medication during the visit.

In this paper, we are interested in the behavioral responses of the medical professionals to potential negative income pressure. This pressure would arise from the threat of loss of patients that are not satisfied by the medical professionals prescription decision. This potential prescription decision response to pressure placed on their income by their clients serves as a problem in the system of control set up to avoid the misuse of the controlled medications.

A salient example of the class of controlled medications is antibiotics. It is widely acknowledged in the medical field that antibiotic resistance (ABR) is increasingly undermining the effective treatment of infections and posing one of the biggest threats to health care (Cars, 2014). In April 2014, the WHO declared that the problem of ABR threatens the achievements of modern medicine. The report by the WHO highlighted that a post-antibiotic era — in which common infections and minor injuries can kill — is a very real possibility for the 21st century (Nathan and Cars, 2014). Examples of services that could no longer be delivered safely without effective antibiotics are major surgery, cancer treatment, prophylaxis in Cesarean sections, and the treatment of pneumonia. These examples show that antibiotic resistance has the potential to fundamentally change the functioning of health systems as we know them (Tomson and Vlada, 2014). These concerns apply to the aggregate welfare of the economy and not necessarily imply any disadvantage to the welfare of an individual who has been prescribed antibiotics. As it relates to the aggregate cost, the annual dead-weight loss associated with outpatient prescriptions for amoxicillin (an antibiotic) in the United States is estimated at $225 million Elbasha (2003).

The analysis of Cantrell et al. suggests that around 11 million of prescriptions in the USA are inappropriate and estimates a waste of health care resources up to US$ 281 millions (Filippinia et al., 2003). With the recently enacted Affordable Care Act (ACA), there is increased potential for moral hazard, and access to care for a large number of the population, where the cost of medical care is decreased for these individuals. As a result of this increased moral hazard it is reasonable to question the impact of the increased medical access on the problem of ABR. In an attempt answer that question, this paper estimates the impact of the price of a doctors visit on the demand for antibiotics.

Prior literature suggests that the Affordable Care Act (ACA) will have modest effects on the demand for health services (Glied and Ma, 2015). This dampened effect is supported by the findings that cost-sharing is an imprecise way to reduce less appropriate care. The reductions in medical care utilization were spread across situations where medical treatment would be highly effective (an infection that can be treated with antibiotics) and where medical treatment would likely provide the fewest benefits - a flu caused by a virus- (Lohr et al., 1986). From the RAND HIE, it was found that prescription drug use is responsive to cost-sharing. The reduction in drug expenditures, however, can be attributed in large part to the differences in visit cost-sharing rates (Jeanne et al., 2002).

This paper determines the impact that the additional cost of visiting a doctor in order to obtain a prescription, has on the demand for antibiotics. The paper begins with the theoretical analysis based on the impact of the law of demand on the part of the patients. That is, as the doctor visit price faced directly by the patient decreases, the demand for the doctors services will increase. This increase in the potential number of patients seeking the services of the physician, will lead to a decreased income pressure faced by the physician. Hence, the question is does the level at which the physician prescribes antibiotics change as their income pressure changes. This paper differs from most studies on physician induced demand, as it focuses income stability through the means of the extensive margin - increased number of patients - as opposed to the increase in the intensive margin of care given.

The doctor's revenue per visit elasticity of the doctor visit on the demand for antibiotics plays an important role in the determination of the impact of this increased moral hazard on the demand for antibiotics. Where a positive doctor's revenue per visit elasticity value suggests that the level of prescribed antibiotics decreases in response to the reduced income pressure from lower quantity of patients. Where the pressure to please patients in order to keep them as patients is reduced. The RAND HIE found that antibiotics were very price responsive, Schiff (2001) and the paper by Chandra et al. (2010) found that this response was mostly through physician visits. This would suggest that the mechanism by which the populace demand for antibiotics is susceptible to moral hazard, and this is relevant because of the higher moral hazard susceptibility resulting from the ACA.

The model developed for the impact on demand for health care by the change in prices done in Meyerhoefer and Zuvekas (2009) provides a clearer path, than the Ellis (1986) paper, to the derivation of the demand for prescription drugs being done in this paper. The model used in Meyerhoefer and Zuvekas (2009) involves an intricate compilation that takes advantage of the panel structure of the data. This paper uses a simplified version of the model that does not use the panel structure of the data, in an effort to produce base estimates. The derived and empirically implemented demand model in this paper involves a probit model, because the dependent variable in the model analyzed in this paper is a dichotomous variable, and not a count variable.

4.2 Conceptual/Theoretical Model

This analysis determines the impact of the additional cost of the doctor visit. To do this, this paper models the demand for the antibiotic medication as a function of the necessary variables including the visit to the doctor to acquire a prescription for the antibiotic. The demand equation results from the theoretical model of the demand for good health presented in Grossman (1972). In this model, Grossman (1972) presents health as a durable capital stock that yields an output of healthy time. Individuals $i = 1, ..., N$ inherit an initial amount of this stock that depreciates with age and can be increased by investment in medical services, $m_{kit}, k = 1, ..., K$. The production function of health with random shocks, ϵ_{it} can be presented as the following, as shown in Meyerhoefer and Zuvekas (2009):

$$H_{it} = h(H_{it-1}, m_{1it}, ..., m_{Kit}, \epsilon_{it}) \tag{5}$$

Meyerhoefer and Zuvekas (2009) defines the utility function for an individual $i = 1, ..., N$ who has preferences over health and a composite commodity of all other goods, as the following:

$$U_i = U(H_i, C_i) \tag{6}$$

Individuals $i = 1, ..., N$ choose their investment in health (via medical services) and their level of consumption of other goods that maximizes their utility shown in equation (6) subject to the following budget constraint:

$$\sum_k p_{kit} m_{kit} + C_{it} \leq Y_{it} \tag{7}$$

where Y_{it} is the total disposable income, p_{kit} is the price for the medical service k faced by the person i in the time period t, and the price of the composite commodity has been normalized to one Meyerhoefer and Zuvekas (2009). The demand equations that represent the optimal level of medical services, and includes exogenous socio-demographic determinants Z_{it} is as follows:

$$m_{kit} = q(p_{1it}, ..., p_{Kit}, Y_{it}, \epsilon_{it}; Z_{it}) \tag{8}$$

The medical service of concern in the paper is the prescription drug, antibiotics. Therefore the value of k is set to one.

The price of the medical services used in this paper is the average total price of the medical service. This price is a biased estimation of the true shadow price of the medical services. This bias results because the average price does not account for the individuals expectation of on the their level of future utilization. The need to account for the expectation of the individual results from the presence of medical insurance and the nonlinear pricing schedules that come with it. Meyerhoefer and Zuvekas (2009) The estimated average price could result in an upward bias of the estimated impact due to the problem of endogeneity, where the propensity of use is not accounted for in the estimated price Meyerhoefer and Zuvekas (2009).

In order to minimize the heterogeneity of the type of prescription drugs provided, the analysis done in this paper is limited to individuals with the medical condition, common cold, with an ICD9 code of “460”.

4.3 Empirical Approach

The analysis done in this paper uses a demand equation for the prescription medication, antibiotics, among individuals who reported having a common cold.

The following antibiotics demand equation will be estimated using a Probit model.

$$\text{antibi}_{vitr} = \beta_1 \text{unins}_{vitr} + \beta_2 \text{RXXP}_{vitr} + \beta_3 \text{OBXPX}_{vitr} + \text{Z}'_{vitr}\alpha + \text{T}_t + \text{R}_r + u_{vitr} \quad (9)$$

where antibi_{vitr} is an indicator variable that equals one for visit (v), of individual (i), who reported having a common cold and used the antibiotics as a course of treatment in year (t) and region (r). The variable unins_{vitr} is an indicator variable that equals one for individuals who do not have insurance coverage, and zero for the individuals who have any form of insurance. The average total price of the antibiotics for each individual is measured by the variable RXXP_{vitr}. The measure of the average total price of office based visit made to the doctor is represented by the variable OBXPX_{vitr}, for each individual.

The variable RXXP_{vitr} is used to measure the own-price elasticity of antibiotic medication on the demand for antibiotics. The variable $OBXPX_i$ is used to measure the provider's revenue per visit elasticity of doctor visit on the demand for antibiotics. This variable indirectly shows the impact of access to care on the demand for antibiotics, and its possible role in the progression of antibiotic resistance (ABR). The variable unins_{vitr} is included in the core variables used in the analysis done in this paper, in order to directly estimate the impact of gaining insurance on the demand for antibiotics. This relates to the impact of the increase of the access to care created by the newly enacted ACA, on the issue of ABR.

The variable Z_{vitr} is a vector of the individual's demographic variables for each observation in the sample. The demographic variables used in this analysis are: age, the squared value of age divided by 100, race (equals one if the individual is White and zero otherwise), gender (equals one if the individual is female, and zero otherwise), ethnicity (equals one if the individual is Hispanic and zero otherwise). Also includes: education status variables (equals one if the individual has up to a high school diploma, a college completed education, more than a completed college education, and zero if not), physical health status based on the individual's perception of their physical health status (either poor, moderate, or excellent), and mental health status (either poor, moderate, or excellent) based on the individual's perception of their own mental health.

T_t represents the year fixed effects, where each year has a dichotomous variable included in the equation. This is to control for any possible impact on individual use of antibiotics that is due to the year in which the event occurred.

R_r represents the fixed effects for each of the four regions in the dataset, where each region has a dichotomous variable included in the equation. This is to control for any possible impact on individual use of antibiotics that is due solely to the region in which the prescription medicine event occurred.

The estimation of equation 9 is weighted using the final person weight, called PERWTF in the household component data of MEPS. The standard errors are heteroskedastic-robust.

4.4 Data

The analysis of the derived demand model in this paper is done using the Medical Expenditure Panel Survey (MEPS). This data set is a nationally representative survey of the US civilian, non-institutionalized population. The MEPS data has a series of public use event files from the Medical Expenditure Panel Survey Household Component (MEPS HC) and Medical Provider Component (MPC). Two of such event files are used in this analysis. The first is the Prescribed Medicines (PMED) File which provides detailed information on household-reported prescribed medicines that can be used to make estimates of prescribed medicine utilization and expenditures for each calendar year (AHRQ, 2014). The second file is the Medical Conditions File, which provides information on household-reported medical conditions. Each record represents one medical condition reported for a household survey member who resides in an eligible responding household and who has a positive person or family weight. Additional, the office-based medical provider visits events file was used in this paper to determine the types of medicine prescribed, and expenditures of the office visit.

The sample used for this analysis span the years 2004 through 2010. It is pooled, and thus no special econometric treatment was used to take advantage of the length and panel structure of the data. The sample is measured at the condition level where each observation shows the individual demographics related to the reported condition. Each observation also contains information about the medication - if any - that was prescribed to treat the reported condition. There are observations where no medication was prescribed to treat the related condition.

In order to analyze the effect of the price of the doctor visit on the demand for the antibiotics, the data used in the analysis is limited to the individuals who report having the condition; common cold. One of the reasons for this modeling choice is the medical theory that the common cold cannot be treated with antibiotic medication

(Jefferson and Tyrrell, 2001). Additionally, upon inspection of the data, the common cold is the most frequently occurring condition for which antibiotics are prescribed. Figure 7 shows the top five conditions for which antibiotics are prescribed and their frequency; it shows that the ICD9 code 460 occurs the most frequently.

The price paid for the prescription by the individuals who purchased the prescribed antibiotics is acquired from the PMED event file. The price paid for the office based visit is available for the individuals who did go the office of the health care provider. In order to impute the price of the office visits for the individuals who did not go to provider for a given condition, data from both the PMED event file and the office visits event file were used to calculate the average total price of the office-based physician visit, and the average total price of the prescribed medication paid for each insurance category. The calculated averages are then imputed for the individuals who reported having the relevant condition, but did not visit a doctor.

The descriptive statistics of the variables used for the analysis done in this paper are shown in table 13. There was total number of 8,374 individuals who had a common cold, over the years of 2004 through 2010. The main dependent variable in this analysis is an indicator variable that equals one if the treatment received for the common cold is an antibiotic. The average value of this antibiotic use is 16.31%. This means that for 16.31% of the 8374 reported cases of the common cold an antibiotic prescription was used for treatment. From the descriptive statistics table, we see that approximately 10% of the individuals who had a common cold, were black. The number is similar for Hispanics in the data, where approximately 11% of the individuals who had a common cold in the sample were Hispanics.

On average, there are more women who had the common cold condition, than there are men. Interestingly, in the sample, 85% of the individuals who had a common cold live in the urban parts of the country. More than half the sample of individuals who had a common cold reported having excellent mental health status, with approximately 36% reporting excellent physical health.

The descriptive statistics table shows that only approximately 4.3% of the people who reported having a common cold were uninsured. This signals that any impact on the ABR that would arise from the increase in access to care by the ACA for this group of individuals, should not be as significant given the low proportion of uninsured. The average family income per adult equivalent of the individuals who have reported the condition of the common cold is approximately $30,500. This value is relatively high, which corresponds to the high proportion of urban residents, the low proportion of uninsured individuals, and the low proportion of Black and Hispanic individuals in the data.

The value for the mean of the total price of the antibiotics, reported in the table of descriptive statistics is approximately $57, where the lowest value is $47.28 and the highest value is $79.78. The price of the office based doctor visits are considerably higher. The value for the mean of this variable, reported in the table of descriptive statistics, is approximately $149. Its lowest value is $104.63 and the highest value is $160.14.

4.5 Empirical Results

Visual inspection the summary statistics would suggest that the findings by Chandra et al. (2010) are supported by this analysis sample. However, the results found and presented in this section contradict the findings. It should be noted that this difference in findings could be due to the disproportionate volume of high socio-economics-status individuals that make up the common cold analysis sample.

The estimated values using the Probit model are shown in table 14. The positive sign on the doctor's revenue per visit variable suggests that as the price of the doctor visits decreases, the probability of using antibiotics as a treatment for common cold decreases. This supports the model that the doctors are responding to the increased income pressure by prescribing antibiotics for colds when they are not necessary.

The estimated own-price and provider's revenue per visit elasticities are represented in table 15. These estimates suggest that the individuals in the data are very sensitive - higher elasticity - to changes in the price of the office based doctor visits, than they are to the price of the antibiotics. This result is understandable given the difference in the average price the antibiotic medication when compared to the price of the office-based visit. These estimates, however, are not statistically significant. Therefore, the probability of receiving antibiotics for the treatment of the common cold responds to the change in neither the price of the medication itself nor the price of the office-based doctor visit.

The estimated elasticity on insurance coverage variable, shown in table 15 suggests that the demand for antibiotics is not sensitive to changes in an individuals insurance status. This results supports the conclusion that the enactment of the

ACA will not have a negative welfare outcome with regard to increase the demand for antibiotics, and with it the rate of ABR.

The only demographic variables that have statistical significance in this estimated model are age, age squared divided by 100, Midwest, South, log of total family income per adult equivalent, and reporting poor physical health. The age and age squared variables are statistically significant at the 10% level of significance. The age squared variable also suggests that there is a convex - to the independent variable - relationship (with a minimum age of 62) between the age of the individual and the probability of using antibiotics to treat the common cold. This suggests that the problem of ABR is increases as the individual increases in age, as the inappropriate use increases - making it a significant threat of the elderly. . On the other hand, a majority of the individuals for which the ACA created access of care, are of the non-elderly population due to existence of Medicare, which implies that there is lower cause for concern of the impact of the extension of the ACA on the problem ABR.

The estimate on the log of total family income variable suggests that a one percent increase on total family income, increases the probability of using antibiotics to treat the common cold by 0.059. This estimated value is statistically significant at the 10% level of significance. The result here could suggest the indirect impact of education on the ability to manipulate the medical system more effectively as relayed in the health demand model proposed by Grossman (1972). This is assuming that more educated individuals have higher total family income. This notion of effectiveness found here corresponds to the message being promulgated in the medical field on the necessity of promoting ABR education to the patients, as a tool necessary for the reduction in the abuse of antibiotics Nathan and Cars (2014). Reporting a health status of poor physical health, statistically significantly decreases the probability of using antibiotics to treat the common cold by 0.406 versus reporting a health status of moderate physical health.

A unit increase on the price of the antibiotics, decreases the probability of treating the common cold with an antibiotic by 0.058. A unit increase in the price of the office based doctor visits, increases the probability of treating the common cold with an antibiotic by 0.006. The estimated impacts on both price variables are statistically insignificant. One of the reasons includes the variables included in this analysis. As a follow-up to the analysis performed in this paper, we will not include the own price variable in the analysis because that price does not necessarily impact the doctors decision to prescribe medication.

4.6 Discussion and Conclusions

There is a large literature on factors contributing to the social misuse of antibiotics by both pediatric and adult patients (McDonnell, 2008; Bauchner et al., 1999; Macfarlane et al., 1997). One driver is physician-prescribing practices. Studies show that physicians vary broadly in their antibiotic prescription practices, and may not be aware of or adhere to clinical practice guidelines addressing proper use of antibiotic agents (Halm et al., 2001).

A positive value of the doctor's revenue per visit elasticity means that as the price of the visit to physician's office decreases, the number of antibiotic prescriptions for the treatment of the common cold decreases as well. The decrease in the price of the visit to the physician should increase the number of people visiting the physician, according to the law of demand, where the as the price of a good decreases the quantity demanded of that good increases. Therefore, everything else held constant, if the number of people visiting the physician increases when the price drops, it should follow that the number of antibiotics prescriptions would increase as well. However, the positive value of the doctor's revenue per visit elasticity implies that as the price of the visit decreases the number of antibiotic prescriptions decrease as well.

This interpretation suggests that the number of prescribed antibiotics changes in response to the reduced income pressure that would result from a lower quantity of patients. Where an increase in the price of the office visit makes the income from the patients who visit important - as there isn't as much a demand for the service to treat common cold with the higher visit price. Therefore, a decrease in the price of the visit would increase the quantity demanded of office visits, and thus reduce any pressure to maintain income levels.

In order for the positive value of the provider's revenue per visit elasticity to imply the above improper prescription of antibiotics to be true given this analysis sample, the estimate will need to be statistically significant. This is however, not the case in this discovered in this research. That is, the results of this paper shows that physicians are not improperly prescribing antibiotics in response to changes in their price of their services, at a statically significant level. There are most likely other driving forces for the prescription behavior of the physicians, such as the patients demanding antibiotic agents in inappropriate clinical situations. Patient demand for antibiotics in the setting of viral or non-infectious diseases can promote resistance, as studies have shown that prescription of multiple courses of the same antibiotic selects for more resistant organisms.

The results of the paper also showed that the patients demand for antimicrobials for the treatment of the common cold is not statistically affected by changes in the price of the antimicrobials. This could be due to the notion where antibiotics have long been seen as cheap drugs. For example, Wal-Mart's low-cost program allows patients to buy 12 different varieties of the antibiotic amoxicillin for $4 per month[13]. This implies that something other than the price of the antibiotics should be considered when working towards elimination of the antibiotics resistance occurrences.

In September 2014, the U.S. President's Council of Advisors on Science and Technology released a report on antibiotic resistance linked to an executive order from President Obama, who directed the National Security Council to work with a governmental task force and a nongovernmental advisory council to develop a national action plan by February 2015. Among other goals, the plan proposed an implementation of antibiotic stewardship in health care facilities and the community; development of rapid, point-of-care diagnostics; recruitment of academic and industry partners to increase the pipeline of antibiotics, vaccines, and alternative approaches; and international collaboration for prevention, surveillance, and control of antibiotic resistance Nathan and Cars (2014) .

[13]See Wal-Mart $4 Medication List. http://www.usatoday.com/money/industries/health/drugs/walmart-druglist.pdf (last visited May 31, 2019)

When compared to the impact of the increased access to care instigated by the Affordable Care Act (ACA), these actions mentioned above are items that would have more of a direct impact on the progression of the antibiotic resistance (ABR), and in this case the impact can be expected to be positive, which would lead to a slowdown of its progression.

Figure 7: Most Occurring Conditions treated by Antibiotics

Condition Name	ICD-9-CM CODE FOR CONDITION - EDITED	Freq.	Percent	Cum.
Acute Nasopharyngitis (Common Cold)	460	560	5.4	5.4
otitis media - Middle Ear Infection	382	428	4.12	9.52
Enteritis - Intestinal infections	8	413	3.98	13.5
Essential hypertension	401	359	3.46	16.96
SINUSITIS - Sinus Infection	473	326	3.14	20.1

Table 13: Sample Summary Statistics

Variables	Mean	Min	Max
Antibiotics Prescription	0.1631	0	1
Total Price of the Antibiotic	56.56	47.28	79.78
Total Price of the Office-Based Visit	148.59	104.62	160.14
Demographic Variables			
Age	36.98	0	85
(Age_Square) ÷ 100	19	0	72.25
Hispanic	0.1064	0	1
Black	0.1034	0	1
White	0.8459	0	1
Other Race	0.0507	0	1
Female	0.5941	0	1
Midwest	0.3035	0	1
South	0.2916	0	1
West	0.2322	0	1
Northeast	0.1727	0	1
Urban	0.8524	0	1
High School Diploma	0.1490	0	1
Some College	0.1789	0	1
Bachelors	0.1868	0	1
Bachelors - Plus	0.0929	0	1
Ln(Total Income)	10.3271	-0.8959	12.573
Poor Physical Health	0.2215	0	1
Excellent Physical Health	0.3604	0	1
Poor Mental Health	0.1610	0	1
Excellent Mental Health	0.5413	0	1
Uninsured	0.0426	0	1

Notes: The number of observations for the entire sample is 8,374.

Table 14: Estimation Results: Probit

Variable	Margins (ey/ex)	(Std. Err.)
Age	-0.036**	(0.011)
(Age_Square) ÷ 100	0.029*	(0.014)
Hispanic	-0.075	(0.114)
Black	0.037	(0.174)
Other Race	0.111	(0.141)
Female	-0.052	(0.091)
Midwest	0.222*	(0.107)
South	0.255*	(0.116)
West	0.089	(0.126)
Urban	0.057	(0.104)
High School Diploma	-0.058	(0.153)
Some College	-0.202	(0.163)
Bachelors	-0.109	(0.193)
Bachelors - Plus	0.043	(0.192)
Ln(Total Income)	0.059*	(0.027)
Poor Physical Health	-0.406**	(0.147)
Excellent Physical Health	0.103	(0.113)
Poor Mental Health	-0.116	(0.206)
Excellent Mental Health	0.066	(0.116)
Uninsured	2.768	(2.054)
Total Price of the Antibiotic	-0.058	(0.183)
Total Price of the Office-Based Visit	0.006	(0.053)
Observations	8374	
SE	Robust	
Weighted	Yes	
YearFE	Yes	
RegionFE	Yes	

Notes: The standard errors are heterogeneously robust. Robust standard errors in brackets (*** p<0.01, ** p<0.05, * p<0.1). The control variables used in these regression models include year indicator variables for the years 2004 to 2010, region indicator variables for the Northeast, West, Midwest, and South regions. The demographic variables of the individuals in the sample controlled in the model are gender, race, socio-economic status, ethnicity, and insurance status, and perceived physical & mental health. The data are weighted using the reported final person weight assigned to each individual. The data is sourced from MEPS administered by AHRQ.

Table 15: Own-Price and provider's revenue per visit Elasticities

Total Price of the Antibiotic Prescription	-1.5048	[1.2829]
Total Price of the Office-Based Visit	0.6325	[0.5526]
Uninsured	0.2242	[0.1618]

Notes: The standard error is in parenthesis. These standard errors were estimated using the Delta-method. (*** p<0.01, ** p<0.05, * p<0.1).

References

AHRQ (2008a). Meps hc-104 - full year consolidated data file.

AHRQ (2008b). Meps hc-104 - medical conditions.

AHRQ, A. f. H. R. (2009). Medical expenditure panel survey background.

AHRQ, A. f. H. R. (2014). Medical expenditure panel survey public use file details.

AHRQ, A. f. H. R. (2015). Medical expenditure panel survey survey questionnaires.

AHRQ, A. f. H. R. (2017). Medical expenditure panel survey download data files.

AHRQ, A. f. H. R. (2018). Medical expenditure panel survey home.

AHRQ, A. f. H. R. and Quality (2014). Medical expenditure panel survey public use file details.

Almond, D., Doyle, Jr., J. J., Kowalski, A. E., and Williams, H. (2010). Estimating marginal returns to medical care: Evidence from at-risk newborns*. *The Quarterly Journal of Economics*, 125(2):591–634.

Anderson, M., Dobkin, C., and Gross, T. (2012). The effect of health insurance coverage on the use of medical services. *American Economic Journal: Economic Policy*, 4(I):1–27.

Andrews, M. (2013). Options for young adults: Stay on the folks' plan, move to the marketplace or go without.

Anomaly, J. (2010). Combating resistance: The case for a global antibiotics treaty. *Public Health Ethics*, 3(1):13–22.

Austin, D. J., Kristinsson, K. G., and Anderson, R. M. (1999). The relationship between the volume of antimicrobial consumption in human communities and the frequency of resistance. *Proceedings of the National Academy of Sciences*, 96(3):1152–1156.

Bauchner, H., Pelton, S. I., and Klein, J. O. (1999). Parents, physicians, and antibiotic use. *Pediatrics*, 103(2):395–401.

Baum, C. F., Schaffer, M. E., and Stillman, S. (2018). Extended instrumental variables/2sls, gmm and ac/hac, liml and k-class regression.

Belongia, E. A., Naimi, T. S., Gale, C. M., and Besser, R. E. (2002). Antibiotic use and upper respiratory infections: A survey of knowledge, attitudes, and experience in wisconsin and minnesota. *Preventive Medicine*, 34(3):346–352.

Boquiren, V. M., Hack, T. F., Beaver, K., and Williamson, S. (2015). What do measures of patient satisfaction with the doctor tell us? *Patient Education and Counseling*, 98(12):1465–1473.

Bureau, U. C. (2018). 2010 census regions and divisions of the united states.

Cameron, A. C. and Trivedi, P. K. (2017). *Microeconometrics Methods and Applications*. Cambridge University Press.

Carmeli, Y., Eliopoulos, G., Mozaffari, E., and Samore, M. (2002). Health and economic outcomes of vancomycin-resistant enterococci. *Archives of Internal Medicine*, 162(19):2223–2228.

Cars, O. (2014). Securing access to effective antibiotics for current and future generations. Whose responsibility? *Upsala Journal of Medical Sciences*, 119(2):209–214.

CDC (2017). Emerging infectious diseases journal - cdc.

CDC, C. f. D. C. . P. (2019a). National antimicrobial resistance monitoring system for enteric bacteria (narms) — narms — cdc.

CDC, C. f. D. C. . P. (2019b). National antimicrobial resistance monitoring system (narms) now: Human data.

Cerner (2019). Drug database.

Chandra, A., Gruber, J., and McKnight, R. (2010). Patient cost-sharing and hospitalization offsets in the elderly. *American Economic Review*, 100(1):193–213.

Chemistry-LibreTexts (2018). Propagation of error.

Clever, S. L., Jin, L., Levinson, W., and Meltzer, D. O. (2008). Does doctor-patient communication affect patient satisfaction with hospital care? results of an analysis with a novel instrumental variable. *Health Services Research*, 43(5p1):1505–1519.

Cohen, J. W., Cohen, S. B., and Banthin, J. S. (2009). The medical expenditure panel survey. *Medical Care*, 47(Supplement):S44–S50.

Collins, S. R., Schoen, C., Kriss, J. L., Gould, E. M., and Mahato, B. (2008). Rite of passage? why young adults become uninsured and how new policies can help. *Commonwealth Fund Issue Briefs*, 38:1–24.

Elbasha, E. H. (2003). Deadweight loss of bacterial resistance due to overtreatment. *Health Economics*, 12(2):125–138.

Ellis, R. P. (1986). Rational Behavior in the Presence of Coverage Ceilings and Deductibles. *The RAND Journal of Economics*, 17(02):158–175.

Eng, J. V., Marcus, R., Hadler, J. L., Imhoff, B., Vugia, D. J., Cieslak, P. R., Zell, E., Deneen, V., Mccombs, K. G., Zansky, S. M., and et al. (2003). Consumer attitudes and use of antibiotics. *Emerging Infectious Diseases*, 9(9):1128–1135.

Filippinia, M., Masieroa, G., and Moschettia, K. (2003). Socioeconomic determinants of regional differences in outpatient antibiotic consumption: Evidence from Switzerland. *Health Policy*, 78(1):77–92.

Freeman, T. (2002). Using performance indicators to improve health care quality in the public sector: A review of the literature. *Health Services Management Research*, 15(2):126–137.

Glied, S. and Ma, S. (2015). The need to look at antibiotic resistance from a health systems perspective. *The COMMONWEALTH FUND*.

Goossens, H., Ferech, M., Stichele, R. V., and Elseviers, M. (2005). Outpatient antibiotic use in europe and association with resistance: a cross-national database study. *The Lancet*, 365(9459):579–587.

Granizo, J. J., Aguilar, L., Casal, J., Dal-Ré, R., and Baquero, F. (2000). Streptococcus pyogenes resistance to erythromycin in relation to macrolide consumption in spain (1986–1997). *Journal of Antimicrobial Chemotherapy*, 46(6):959–964.

Grossman, M. (1972). On the concept of health capital and the demand for health. *Journal of Political Economy*, 80(2):223–255.

Halm, E. A., Switzer, G. E., Mittman, B. S., Walsh, M. B., Chang, C.-C. H., and Fine, M. J. (2001). What factors influence physicians' decisions to switch from intravenous to oral antibiotics for community-acquired pneumonia? *Journal of General Internal Medicine*, 16(9):599–605.

Harrison, J. M., Lagisetty, P., Sites, B. D., Guo, C., and Davis, M. A. (2018). Trends in prescription pain medication use by race/ethnicity among us adults with noncancer pain, 2000–2015. *American Journal of Public Health*, 108(6):788–790.

Healthcare.gov (2012). Health insurance coverage for children and young adults under 26.

Imbens, G. W. and Lemieux, T. (2008). Regression discontinuity designs: A guide to practice. *Journal of Econometrics*, 142(2):615–635.

Jain, M. (2010). Chapter-01 antimicrobial choice for disease conditions. *Management of Infectious Diseases*, page 1–114.

Jeanne, R., Hosek, S., Vollaard, B., and Mahnovski, S. (2002). The Elasticity of Demand for Health Care: A Review of the Literature and Its Application to the Military Health System. *RAND Corporation*.

Jefferson, T. O. and Tyrrell, D. (2001). Antivirals for the common cold.

Johnson, J. K., Smith, G., Lee, M. S., Venezia, R. A., Stine, O. C., Nataro, J. P., Hsiao, W., and Harris, A. D. (2009). The role of patient-to-patient transmission in the acquisition of imipenem-resistantpseudomonas aeruginosacolonization in the intensive care unit. *The Journal of Infectious Diseases*, 200(6):900–905.

Kesselheim, A. S. and Outterson, K. (2011). Improving antibiotic markets for long term sustainability,. *Yale Journal of Health Policy, Law, and Ethics*, 11(1):101–168.

Kupfer, J. M. and Bond, E. U. (2012). Patient satisfaction and patient-centered care. *Jama*, 308(2):139.

Lee, D. S. and Card, D. (2008). Regression discontinuity inference with specification error. *Journal of Econometrics*, 142(2):655–674.

Lee, D. S. and Lemieux, T. (2010). Regression discontinuity designs in economics. *Journal of Economic Literature*, 48(2):281–355.

Levy, S. B. (2000). Antibiotic and antiseptic resistance: impact on public health. *The Pediatric Infectious Disease Journal*, 19(Supplement).

Macfarlane, J., Holmes, W., Macfarlane, R., and Britten, N. (1997). Influence of patients expectations on antibiotic management of acute lower respiratory tract illness in general practice: questionnaire study. *Bmj*, 315(7117):1211–1214.

McCrary, J. (2007). Manipulation of the running variable in the regression discontinuity design: A density test. Working Paper 334, National Bureau of Economic Research.

McDonnell, N. G. (2008). Antibiotic overuse: The influence of social norms. *Journal of the American College of Surgeons*, 207(2):265–275.

Mcgowan Jr, J. E. (2001). Economic impact of antimicrobial resistance. *Emerging Infectious Diseases*, 7(2):286–292.

MEPS (2013). Multum lexicon addendum files to meps prescribed medicines files 1996-2013.

Meyerhoefer, C. D. and Zuvekas, S. H. (2009). New Estimates of the Demand for Physical and Mental Health Treatment. *Health Economics*.

Michael, C. A., Dominey-Howes, D., and Labbate, M. (2014). The antimicrobial resistance crisis: Causes, consequences, and management. *Frontiers in Public Health*, 2(145).

Nathan, C. and Cars, O. (2014). Antibiotic Resistance — Problems, Progress, and Prospects. *New England Journal of Medicine*, 371(19):1761–1763.

Palmieri, G. (2017). Benefit spotlight: Milestone birthdays that matter for dental and vision coverage.

Riiskjær, E., Ammentorp, J., Nielsen, J. F., and Kofoed, P.-E. (2010). Patient surveys—a key to organizational change? *Patient Education and Counseling*, 78(3):394–401.

Roffman, C. E., Buchanan, J., and Allison, G. T. (2016). Charlson comorbidities index. *Journal of Physiotherapy*, 62(3):171.

Rouse, M. (2014). What is icd-9-cm (international classification of diseases, ninth revision, clinical modification) ? - definition from whatis.com.

Schiff, G. (2001). Free for all?: Lessons from the rand health insurance experiment. *Journal of Public Health Policy*, 22(2):244–247.

Schmidheiny, K. (2018). Instrumental variables - short guides to microeconometrics.

Schwartz, K. and Damico, A. (2010). Aging out of medicaid: What is the risk of becoming uninsured?

Shiel, W. C. (2018). Definition of antimicrobial.

Squires, S. (2012). Patient satisfaction: How to get it and how to keep it. *Nursing Management (Springhouse)*, 43(4):26–32.

Sun, L., Klein, E. Y., and Laxminarayan, R. (2012). Seasonality and temporal correlation between community antibiotic use and resistance in the united states. *Clinical Infectious Diseases*, 55(5):687–694.

Sydnor, E. R. M. and Perl, T. M. (2011). Hospital epidemiology and infection control in acute-care settings. *Clinical Microbiology Reviews*, 24(1):141–173.

Tomson, G. and Vlada, I. (2014). The need to look at antibiotic resistance from a health systems perspective. *Upsala Journal of Medical Sciences*, 119(2):117–124.

Trochim, W. (1984). *Research Design for Program Evaluation: The Regression-Discontinuity Design*. SAGE Publications, Inc.

U.S.EPA (2017). What are antimicrobial pesticides?

Wang, L. Y., Zhong, Y., and Wheeler, L. (2006). Asthma medication use in school-aged children. *Journal of Asthma*, 43(7):495–499.

WHO (2017). What is antimicrobial resistance?

WHO (2018). Antibiotic resistance.

Zuckerman, I. H., Lee, E., Wutoh, A. K., Xue, Z., and Stuart, B. (2006). Application of regression-discontinuity analysis in pharmaceutical health services research. *Health Services Research*, 41(2):550–563.

Amy E. Eremionkhale
Curriculum Vitae

Contact Information

13 Duh Dr, Apt 111, Bethlehem, PA 18015
Phone: 716-512-3426 (Mobile)
Email: aee214@lehigh.edu
Homepage: https://amyeremionkhale.com

Education

Expected 2019	Ph.D., Economics, Lehigh University Dissertation Title: *Impact of Price, Income and Externalities on Incentives for Health Care Providers and Patient Behaviors* Dissertation Committee: Shin-Yi Chou (Chair), Todd Watkins, Mary E. Deily, Suhui Li
2012–2014	M.S., University at Buffalo–SUNY Concentration: Financial Economics
2011–2012	M.B.A., Canisius College Concentration: Accounting
2008–2011	B.S., Canisius College Three Majors: Economics, Accounting, and Accouting Information Systems

Research Fields

Primary	Health Economics, Applied Econometrics
Secondary	Labor Economics, and Microfinance

Teaching Experience

Adjunct Professor, Lehigh University,
Department of Economics.
- Applied Microeconomic Analysis: Fall 2018, Summer 2018
- Principles of Economics: Summer 2017

Teaching Assistant, Lehigh University,
Department of Economics,
- Money, Banking and Financial Markets: Spring 2018
- Principles of Economics: Fall 2017

Department of Finance,
- Introduction to Finance: Fall 2014, Spring 2015, Fall 2015, Spring 2016, Fall 2016

Research Experience

Research Assistant, Lehigh University,
Department of Economics: Summer 2018, Spring 2017, Summer 2016, Summer 2015

Research Assistant, University at Buffalo - SUNY,
Department of Economics: Spring 2014, Fall 2013

Working Experience

U.N. Department of Public Information, Non-Governmental Organizations (DPI NGO)
Ex-Officio Member, Executive Committee: Fall 2017 - Present

Center for Public Health (CPH), United Nations, NY
Youth Representative: Fall 2016 - Present

Department of Finance, Lehigh University
Course Assistant, *Introduction to Finance*: Summer 2016, Summer 2015

Department of Economics, University at Buffalo-SUNY
Course Assistant, *Economics of Asset Valuation*: Fall 2013, Spring 2014

Campus Living at Flint Village, University at Buffalo - SUNY
Student Assistant: Spring 2014, Fall 2013, Summer 2013

Women's Business Center, Canisius College
Website and New York State Grant Coordinator: Summer 2012, Fall 2011

Merrill Lynch Bank of America, GWM
Global Wealth Management Intern: Spring 2012

Niagara Frontier Transportation Authority
Accounts Payable Intern: Summer 2011

Lougen Valenti Bookbinder Weintraub (LVBW), CPA LLP
Tax Intern: Spring 2011

Working Papers

1. Eremionkhale, A. "Impact of the Change in Payments on the Actual and Perceived Behaviors of Medical Care Providers". Job Market Paper.

2. Eremionkhale, A. and Watkins, T. "The Effect of the Global Financial Crisis on the Cost Structure and Double Bottom Line Goal of Microfinance Institutions". Submitted.

Work in Progress

1. Eremionkhale, A. and Chou, S. "Negative Externality of Regional Antimicrobial Use".
2. Eremionkhale, A. "Impact of the Price of Physician Visit on the Volume of Prescribed Medicine - A Focus on antibiotics".
3. Eremionkhale, A. "Employment Effects of Increase in Minimum Wage: Evidence from Nigeria".
4. Eremionkhale, A. "Pricing in a market with Electronic and Traditional Commerce".

Awards And Honors

2018	Graduate Student Leadership Award, Lehigh University.
2018	Teaching Assistant of the Year Honorable Mention, Lehigh University.
2017	Teaching Development Program Certificate, Lehigh University
2014-2019	Teaching Assistantship, Lehigh University.
2013	Kogut Brothers research grant, University at Buffalo - SUNY.
2008-2012	Merit Scholarship, Canisius College.

Conference Presentations and Other Activities

Organized Conferences (Presenter)

1. 2019 ASSA Annual Meeting "Impact of Change in Per-Visit Income on the Actual and Perceived Behaviors of Medical Care Providers". Poster Session (Scheduled)
2. 88th Southern Economic Association Annual Meeting, November 2018: "Impact of Change in Per-Visit Income on the Actual and Perceived Behaviors of Medical Care Providers".
3. 44th Eastern Economic Association Annual Meeting, March 2018: "Impact of Change in Per-Visit Income on the Actual and Perceived Behaviors of Medical Care Providers".
4. 87th Southern Economic Association Annual Meeting, November 2017: "The Effect of the Global Financial Crisis on the Cost Structure and Double Bottom Line Goal of Microfinance Institutions".
5. 43rd Eastern Economic Association Annual Meeting, February 2017: "The Effect of the Global Financial Crisis on the Cost Structure and Double Bottom Line Goal of Microfinance Institutions".

Organized Conferences (Chair/Discussant)

1. 44th Eastern Economic Association Annual Meeting, March 2018: Productivity, and Choice (JEL Code I)
   • Session Chair and Discussant of two papers at this conference.

2. 87th Southern Economic Association Annual Meeting, November 2017: Economic Development II
   • Session Chair and Discussant of two papers at this conference.

3. 43rd Eastern Economic Association Annual Meeting, February 2017: Public Policies: Portfolio Choice, Expenditure Patterns and Time Use.
   • Discussant of two papers at this conference.

Invited Presentations

1. Lehigh University (Department of Economics), "Impact of Change in Per-Visit Income on the Actual and Perceived Behaviors of Medical Care Providers", May 2018.

2. Lehigh University (Department of Economics), "The Effect of the Global Financial Crisis on the Cost Structure and Double Bottom Line Goal of Microfinance Institutions", December 2016.

3. Lehigh University (Department of Economics), "Impact of the Price of Physician Visit on the Demand for Prescribed Medicine - A Focus on antibiotics", May 2016.

Skills

Software:	STATA, SAS, R, Mathematica, Maple, LaTeX, Excel VBA (Visual Basic for Applications).
Languages:	English (native), French (limited working proficiency), and Yoruba (minimum professional proficiency)

Service Activities

2017–Present	MLK Committee - Member, Lehigh University.
2016–2017	Graduate Research Committee - Vacation, Maternal and Paternal Policy, Health Insurance Working Group - Member, Lehigh University.
Fall 2017	Economics Department Senate Representative, Lehigh University.
2012-2014	Economics Graduate Student Association - President, University at Buffalo (SUNY).
2010-2012	QuadGear - CEO and COO, Canisius College.
2009-2010	Empire Hall Council - President, Canisius College.
2008-2011	Women's Rugby, Canisius College

Professional Societies and Affiliations

American Economic Association
International Health Economics Association
American Society of Health Economists
Eastern Economic Association
Southern Economic Association
Western Economic Association International

References

Shin-Yi Chou
Author F. Searing Professor of Economics and the Chair of Economics Department,
Lehigh University
Research Associate, National Bureau of Economic Research
Email: syc2@lehigh.edu
Phone: 610.758.3444

Todd Watkins
Arthur F. Searing Professor of Economics
Lehigh University
Executive Director, Martindale Center for the Study of Private Enterprise and Microfinance
Email: watkins@lehigh.edu
Fax: 610.758.4677
Phone: 610.758.4954

Stephen Buell (Teaching)
Professor of Finance
Lehigh University
Co-Director, Integrated Business and Engineering Honors Program (IBE)
Email: steve@lehigh.edu
Fax: 610.758.6429
Phone: 610.758.3436