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Essays on Environmental and Healthcare Economics

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by

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DEDICATION

To my Beloved Family, completion of this Doctoral dissertation would have been impossible without your continued support, guidance, & love.

To the living memories of Dieudonné and Louis Nianogo, your spirit and strength have been with me every step of the way.

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ABSTRACT

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My dissertation comprises three essays in theoretical economics and applied microeconomics. They touch on societal, health and environmental issues from an economic perspective, with the goal of promoting sustainable development and equity. The first essay probes the sources of regional disparities in population health outcomes. I identify the drivers of alternative measures of health outcomes, using data from two specific US regions (the South, which has relatively lower health status; and the Northeast, which enjoys relatively higher health status). Then, using the Blinder-Oaxaca decomposition, I analyze these differences in health outcomes and explore their policy implications. The second essay, exclusively theoretical, models the behavioral reactions of economic agents to climatic change in a stochastic framework. Their reaction toward increasing uncertainties about the damages caused by their pollution levels, as well as the corresponding Pareto equilibrium and its policy implications are computed and discussed. Lastly, the third essay investigates the drivers of prescription drug consumption separately in selected states with low, average, and high prescription drug consumption US states. The noticeable geographic variations in core drivers of health care costs motivate the need to consider separate econometric models. Also to control for the non-normality of healthcare data, the variance stabilizing Box-Cox transformations model is applied.

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CHAPTER 1

INTRODUCTION

My research interest emanates from observations that the greatest challenges of most economies is not the lack of riches, but more so the misappropriation & misallocation of their economic, natural, & human resources. Broadly stated, it put emphasis on the notions of sustainable development on a local, as well as on a more global level. My dissertation comprises four essays, which explore four main subfields of economics: *(1) Environmental issues, (2) health economics, (3) development economics, and (4) the trade-offs between equity and efficiency.*

In the first essay, using 2010-2012 county level data, I investigate regional health disparities in the US northeastern and southern states. The goal of *US Healthy People 2010* is to raise population health status and to reduce disparities. One important source of health disparities is geographic location, which will be the focus of this essay. Past studies investigated how different factors affect US health outcomes. However, health policies from studies not accounting for intrinsic regional differences may mislead. Therefore, this county level investigation focuses on the two distinct US northeastern and southern states. Specifically, population health status in southern states is relatively poor in contrast with the healthier northeastern states. This implies the existence of regional variations in the influence of the determinants of population health status. First, a regional comparison of the determinants of important health outcome measures is undertaken. Obesity and access to care are consistently the most influential determinants of each outcome measure across the regions. Next, using a 3-fold Blinder-Oaxaca decomposition, the regional differences in health outcomes are partitioned into portion explained by each region health factor endowments and the portion unexplained (discrimination). Half of the differences in *clinically-assessed* outcome measures (premature death and low birth weight rates) are unexplained by health endowments. The explained portion for the *self-assessed outcomes* (average number of physically and mentally unhealthy days per month) is small. Study findings justify the need to account for regional variations in constructing economic models of health outcomes to strengthen implications for policy.

The second essay studies the linkage between uncertainties about climate change and global emissions of greenhouse gases, in a theoretical framework. Until recently, uncertainty has mostly been perceived as a "bad". However, Bramoullé and Treich (2009) demonstrate that welfare may increase under uncertainty. They illustrate this possibility with the compelling example of global warming. Greenhouse emissions are affected by two distinct forces. On the one hand, there is a strategic interaction: each country has an incentive to "free-ride" by allowing the other countries to carry the burden of cutting emissions. On the other hand, there is a non-strategic reaction, exclusively due to the uncertainty: a prudent [*in the sense* of Kimball (1993)] country may reduce its emissions when faced with uncertainty about the impact of global warming. The overall impact on welfare depends on whether the strategic effect offsets the effect of uncertainty. In my proposed theoretical essay, I follow B&T in using an n-country Nash equilibrium game in emissions. Using a less restrictive model, I conclude it is not necessarily true that the uncertainty will lower emissions. The impact of uncertainty on a country's decision to reduce (increase) emissions depends on its ordinal preferences (Are the emissions strategic substitutes or strategic complements), as well as on its behavioral response to risk (Is the country prudent proper, cross-prudent). This has two main policy implications. First, at a macroeconomic level, policies of environmental organizations that work to alleviate the risk countries may face, through risk sharing, may not be effective in inducing them to reduce their emissions. Second, it is important to implement different policies across countries, accounting for each country's particular preferences.

In my third essay, I investigate the drivers of prescription drug consumption separately in selected low (ID, SD, and WA), medium (AR, ND) and high (TN) prescription drug consumption US states. Prescription drugs expenditure, currently accounting for 10% of total US healthcare spending, is the third largest and a rapidly growing component of healthcare costs. The 2006 Medicare Part D drug benefits and the 2010 Affordable Care Act are catalysts for further increases in drug spending due to greater insurance coverage. Consequently, this research investigating the drivers of prescription drug consumption is important and timely for its cost containment policy implications. Significant geographic variations in population health status, access to care, socio-economics and demographics, which are core drivers of health care costs; and the cross-state disparities convergence in pharmaceutical expenditures motivate the need to construct and estimate separate econometric models. Since healthcare data tend to be skewed, we fitted the variance stabilizing Box-Cox power family of transformations model to 2010 county-level observations to investigate the drivers of prescription drug consumption separately in low and high drug consumption regions. This innovative study is the first to separately model drug consumption, using the most recent county level data, in these disparate regions. Our study reveals several interesting findings. First, the optimal model λ-power transformation parameter estimates for the dependent variable in high (λ=0.568) Average (λ=0.696), and high (λ=0) spending regions differ significantly. Second, the income elasticity estimates also differ in high (0.536) and low (0.481) spending regions. Third, contrasting the many earlier studies modeling drug expenditures (rather than number of filled prescriptions used in our study) we detect prescription drugs to be a normal good and a technical necessity (the income elasticity for the pooled data model is 0.461) which generally accords with *a priori* theory. Fourth, while the numerical estimates of the extent to which similar factors drive prescription drug consumption differs across regions, access to primary care physicians in the high consumption region is highly statistically significant. Policy implications are explored.

In summary, my goal is to interactively investigate economic issues both theoretically and empirically using solid statistical foundations and to make relevant policy inferences by reconciling the theory to the empirics.

CHAPTER 2

COMPARING AND DECOMPOSING THE DETERMINANTS OF MULTIPLE HEALTH OUTCOMES IN SOUTHERN AND NORTHEASTERN US STATES USING COUNTY DATA

2.1 Introduction

To improve population health outcomes, governments allocate substantial funds toward the health sector. However, the steady growth of the US health expenditures (including hospital care, physician & clinical services, prescription drugs spendings) as a percentage of the Gross Domestic Product (from 13.2% in 2000 to 17.4% in 2009[1]) has not significantly raised population health. Among OECD (Organisation for Economic Co-operation and Development) countries, in United States life expectancy rankings have declined from 14 in 1980 to 25 in 2008 (OECD Health Division, 2011). Moreover, a recent study links about 62% of the bankruptcies filed in 2007 to medical expenses (Himmelstein *et al.* 2009). Altogether, these observations suggesting that the US healthcare system may be "broken also call for a better understanding of the system in order to advocate effective reforms capable of addressing cost inefficiencies and distributional imbalances.

The unhealthy behaviors (smoking and unhealthy habits) of the population, inadequate access to healthcare, and healthcare system deficiencies are among the most prominent reasons why relatively low health outcomes still prevail in the US despites high spending in the healthcare sector. More recently, scholars have linked low health status to health disparities (unfavorable societal conditions). For example, Adler and Rehkopf (2008) find that the US health status is worse for the poor and health disparities vary across outcome measures, time and geographic location (Diez-Roux *et al.*,

1. http://www.oecd.org/health/healthpoliciesanddata/oecdhealthdata2012.htm

2001). Similarly, Isaacs and Schroeder (2004) call for health policies to address all disparities, in addition to improving population health status through public policies that change behaviors and expand insurance coverage to the uninsured and under-insured.

According to the Advisory Committee for Healthy People 2020 (Healthy People 2020), *"Health disparities are systematic, plausibly avoidable health differences adversely affecting socially disadvantaged groups"*. The US Healthy People initiative aims at eliminating these disparities including in geographic location. The present study, focusing on regional health disparities, considers one mortality health outcome measure (premature death) and three morbidity measures (average number of mentally ill-days, number of physically ill-days, and the low birth weight) in two distinct US regions. Our focus regions are southern and northeastern states. The interest in the southern states is justified by the inherently poor population health. Baird (2010) claims that several southern states (Mississippi, Alabama, Arkansas, Louisiana, Tennessee, West Virginia, and Kentucky) have high obesity prevalence (over 30% of the population) and also documents the hypertension and diabetes rates to be among the highest in the US. Interestingly, these states also lag in educational achievements and access to healthcare with higher poverty rates than the rest of the nation. However, in contrast, residents of most northeastern states tend to healthier, more educated and wealthier. Thus, there would be significant regional differences in their health outcomes. The interesting question then will be finding the extent to which these differences could be explained by each region's health factor endowments (e.g., behavioral factors, socioeconomic status, environmental factors, access to care, quality of care, build environment, and demographic variable) or by unmeasured factors that we attribute to regional discrimination.

This study is important for several contributions. First, it identifies the relevant drivers of the different health outcomes in the two distinct US regions (northeastern and southern states) using county level observations. Second, it decomposes differences in the regional health outcomes into the portion explained by health endowments and the portion unexplained. Third, our findings motivate development of policies targeting intervention strategies to each region for reducing regional health disparities.

This research proceeds as follows. Section 2 reviews pertinent literature on the determinant of different health outcomes measures. Section 3 presents the data, defines the variables in the health outcome models, and discusses the research methodology. Section 4 discusses empirical regression estimation results. Section 5 presents results of the Blinder-Oaxaca decompositions. Section 5 explores policy implications of findings and concludes.

2.2 Previous Literature

Health outcomes: Analysis in this work is based on four health outcomes measures: one mortality (potential life-years loss before age 75, YPLL_{75}) and three morbidity (low birth weight rates, number of physically and mentally unhealthy days per month for adults) measures. Of these, only the mean unhealthy days measures are *self-accessed*. Premature death rates capture deaths that could have been avoided had the healthcare system been more efficient. Raw mortality rates in developed countries are mainly driven by a relatively high death rate of the older population (Or, 2000), therefore policies derived from studying these mortality measures could be misleading. The premature death rates can be calculated as follows. First, standard a cut-off age (e.g., 75) is considered assuming that if an individual was able to fully benefit from the healthcare system, she would be expected to reach at least the cut-off age. Second, the number Life-Years Loss (LYL) are obtained by subtracting the age of death i from the cut-off age for specific age groups. Last, the premature death rate is reported per 100,000 by summing the LYL of each age group, weighted by its proportion in the entire population.

Analytically, the premature death rate (YPLL_{75}) can be obtained from the following equation (See, Vila *et al.*,2006):

$$YPLL_{75} = \sum_{i=0}^{75} \frac{\alpha_i d_i (75 - i)}{100000)} \tag{2.1}$$

α_i is the weight of a specific age group in the total population, and d_i the total number of death at age i.

Low birth weight rate[2] is a good indicator of current health status, as well as future health outcome. Individuals weighing less than 2500g at birth are more likely to develop chronic diseases growing up. For example, low birth weight is linked to high blood pressure (Irving et al., 2004), obesity in later years (LA BioMed, 2011) and asthma (Brooks, 2001) in adolescent and adults.

The other morbidity measures (the mean physically and mentally unhealthy days per month for adults) capture health-related quality of life. Despite their fairly extensive use in the literature, few studies have concluded that for the better educated and women, health problems tend to have a stronger effect on these self-reported measures (Delpierre *et al.*, 2009, Salomon *et al.*, 2009). One implication is the tendency to overestimate health disparities in these population groups.

Health behavioral factors: These are well-documented contributing factors to adverse health outcomes. The specific factors of interests are the obesity rates, smoking rates, drinking and exercising habits, as well as the teen-birth rates. An individual whose BMI (Body Mass Index) exceeds 30 is said to be obese. Obesity is known to lessen life expectancy for all races and age groups. Fontaine and *et al.* (2003) estimate that morbid obesity ($BMI > 45$) could lead to 13 and 8 years of life loss, respectively, for 20 years old white men and white women. Similarly, they find 11 and 5 years life

2. a Birth weight of less than 5.5 lbs or 2,500 grams

loss for black men and women, respectively. Obesity also exposes individuals to multiple health risks, such as Type-2 diabetes (McCarthy, 2010), heart disease (Alexander, 2001), cancer (Wolin *et al.*, 2010; Ma *et al.*, 2011), and other complications. The lack of exercise, excessive drinking, and smoking also exacerbate all these conditions. Independently of socio-economic backgrounds, teen pregnancies are more likely to lead to adverse health outcomes both for the mother and the infant. Inadequate prenatal cares, risky behavior during these pregnancies usually lead to pre-term delivery and low birth weight (Chen *et al.*, 2007).

Access to care factors: It is well documented that greater access to the healthcare system and to health providers leads to better health. The main access to care variables is the population percent younger than 65 years without insurance, and the primary care and mental health provider rates. The US Census Bureau, in 2010, estimated that 49.9 million Americans were uninsured and 55.3% of the insured were covered by work-related health insurance (Carmen *et al.*, 2011). Absent other options, uninsured population usually lacks recommended care when facing chronic diseases and consequently will have a lower life span (Andrulis, 1998).

The higher the provider rate in a specific region, the greater is the health care access and expected health outcome.

Quality of care factors: Two measures of the health care quality considered in this study. First is the hospitalization rate for Ambulatory Care Sensitive Conditions (ACSC) capturing preventable hospitalization rates, and second is the percent of diabetic Medicare enrollees who received HbA1c screening, indicating the degree of preventive care in a given population. A high ACSC rate is correlated with the lack of proper primary care and in turn could cause premature deaths (McCall *et al.*, 2001).

Socio-economic and environmental factors: Since more than half the US population has employer-based health insurance there is a significant linkage to education (Winkleby *et al.*, 1992), income (Lochner *et al.*, 2001) poverty and unemployment rate. *"People with higher incomes or personal wealth, more years of education, and who live in a healthy and safe environment have, on average, longer life expectancies and better overall health outcomes*[3] ..

Environmental factors pertain to air quality, availability of healthy food outlets, and liquor store density.

2.3 Data and Methodology

Data

This study employs a 3-year (2010, 2011, and 2012) panel dataset from the County Level Raking (CLR). The rankings are the result of a collaboration of The Robert Wood Johnson Foundation and The University of Wisconsin Population Health Institute. The CLR compiles health outcomes and health factors, at the county level, for all the US states. Specifically, information is provided on various morbidity and mortality health outcomes measures, and health factors sub-grouped into health behavior, clinical care, socio-economic, environmental, and demographic factors (See, Appendix A).

Some variables are omitted from our regression analysis because they are not consistently reported. As earlier indicated, the two US regions of particular interest to this study are counties in the southern (Texas, Oklahoma, Arkansas, Tennessee, N. Carolina, S. Carolina, Louisiana, Mississippi, Alabama, Georgia and Florida) and northeastern (Connecticut, Maine, Maryland, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York and Pennsylvania) states. The research focus in contrasting and comparing these regions emanates from observations that the southern states, on average, have fewer schooling years, earn lower incomes, are more inclined to adopt

3. http://www.nciom.org/wp-content/uploads/NCIOM/projects/prevention/finalreport/Prevention-Chpt11.pdf.

risky health behaviors, and have poor health outcomes.

Descriptive statistics of the data in Table 2.1, by region, for 2010 to 2012, confirm on the one hand, in terms of health outcomes, that the premature death rate is about 33% worse in the south. Also the percent of live births with low birth weight is 2 percentage points higher (9.4 in the south and 7.4 in the northeast). Similarly, adults in the south report more unhealthy days per months. As expected, the 30.7% obesity prevalence in the south is significantly higher than the 26.4% in the northeast. Southern females are 50% more likely to give birth in their teen ages (15-19). The average teen-birth rate per 1000 in the south is 62.7 and 27.4 in the northeast. Access to care measures reveals that the non-Medicare population without health insurance is almost 10 percentage points higher in the south. Moreover, the primary care provider rate per 100,000 of the population is almost 34% greater in the northeast. Also, educational attainments (average freshman graduation rate and the percent of population age 25+ with a 4-year college degree or higher) and unemployment rates are significantly higher in the south. Finally, demographic controls indicate presence of more minorities in the south but the female population percent in both regions is identical.

Table 2.1: Sample Descriptive Statistics, by Region

Focus Area	*Variables*	*Northeast*	*South*
Health Outcome	Premature Death Rate	6,582.79	9,819.32
	Physical Unhealthy Days per month	3.471	4.198
	Mentally Unhealthy Days per month	3.451	3.747
	Low Birth Weight Rate	7.409	9.389
Health Behavior	Obese	26.775	30.771
	Teen-birth Rate	27.444	62.72
Access to Care	Uninsured	13.746	22.937
	PCP	110.493	73.112
	MHP	73.025	8.64
Quality of Care	ACSC	75.624	97.593
	HBA1C	83.889	79.222
Socio-Economic Factors	AFGR	82.354	74.46
	College	41.744	31.105
	Unemployed	7.554	8.579
	Singleparent	22.683	26.94
Environment	Pm days	2.289	1.898
	Ozone days	5.322	2.314
Demographics	Less18	21.566	24.294
	Over65	15.28	14.958
	Black	6.873	18.983
	Hispanic	5.226	11.178
	Female	50.637	50.352
	Rural	43.765	61.006

Model

The goal of this study is to identify the drivers of regional health disparities, to understand how they affect the different health outcomes, and to derive relevant policy inferences. To propose relevant health program and policies capable of reducing adverse health outcome effects, it is important to identify the relevant health factors affecting theses health outcomes the mechanisms through which these health factors affect regional health status. Here, isolating the differences in these health outcomes into those caused by the underlying health factors and those linked to unmeasured characteristics (e.g., regional discrimination, cultural differences) is expected to more insightful[4] . The proposed regression model takes the semi-log functional form:

$$Log(Y_i) = \alpha + X'_{1i}\beta_1 + X'_{2i}\beta_2 + X'_{3i}\beta_3 + X'_{4i}\beta_4 + \mu_i \tag{2.2}$$

With Y the health outcome; X_{ji}, the health factors,i the county considered, and j the health factor group (heath behavior, clinical care, socio-economics, and environmental factors).

Balsa *et al.* (2007) and Hebert *et al.* (2008) stress that treating any difference as disparities, without controlling for the various factors that could lead to these differences is a major shortcoming of the literature on health disparities. To avoid this common pitfall, it is important to identify the relevant health factors for each health outcome and use decomposition techniques to understand the health status differences across regions. In this paper, we use the Blinder-Oaxaca decomposition method [5] (described below) to identify the portion of the regional differences in health outcomes due to unmeasured variables (regional discrimination) and the portion related to the region's own attributes.

Given the two regions (south and northeast), the various health outcome variables Y, and a set of predictors X, how much of the mean outcome differences, R, is accounted for by the group differences in the predictors?

4. Diez-Roux *et al.*, (2001), for example, find that poor neighborhoods have lower health status, independently of race, income, or education.

5. See, Jann , 2008

$$R = E[Log(Y_{NE})] - E[Log(Y_S)] \tag{2.3}$$

$E(Y_i)$ denotes the expected value of the outcome variable.

The mean outcome difference can be expressed as the difference in the linear prediction at the group-specific means of the regressors. That is:

$$R = E(X'_{NE})\beta_{NE} - E(X'_S)\beta_S \tag{2.4}$$

To identify the contribution of group differences in their predictors to the overall health outcomes difference, Equation 2.4 can be rearranged, as follows:

$$R = \underbrace{[E(X_{NE}) - E(X_S)]'\beta_S}_{\text{E}} + \underbrace{E(X'_S)(\beta_{NE} - \beta_S)}_{\text{C}} + \underbrace{[E(X_{NE}) - E(X_S)]'(\beta_{NE} - \beta_S)}_{\text{I}} \tag{2.5}$$

This is a three-fold Blinder-Oaxaca decomposition. The first part $E = [E(X_{NE}) - E(X_S)]'\beta_S$ represents the part of the differential that is due to group differences in the predictors (the "endowments effect"). The second component, the "coefficient effect", $C = E(X'_S)(\beta_{NE} - \beta_S)$ measures the contribution of differences in the coefficients (including differences in the intercept). The third and last term, $I = E(X_{NE}) - E(X_S)]'(\beta_{NE} - \beta_S)$, is an interaction term accounting for the fact that differences in endowments and coefficients exist simultaneously between the two groups.

The decomposition presented in Equation 2.5 is formulated from the viewpoint of the northeastern counties, implying that the group differences in the predictors are weighted by the coefficients of the southern counties to determine the endowments effect (E). In other words, E measures the expected change in mean health outcome of northeastern counties, if the group had southern counties predictor levels. Similarly, for the second component (C), the differences in coefficients are weighted by the south's predictor levels. The second component measures the expected change in the northeastern counties mean health outcomes, if it had the same estimation coefficients as in the southern counties. The differential can analogously be expressed from the viewpoint of the northeastern counties, yielding a reverse three-fold decomposition. The results for each health outcome are next presented.

We also perform the two fold decomposition (proportion explained and proportion unexplained) assuming the existence of a nondiscriminatory coefficients vector, β^*, used to determine each component. In the two-fold decomposition the R can be written as:

$$R = \underbrace{[E(X_{NE}) - E(X_S)]'\beta^*}_{\text{Q}} + \underbrace{E(X'_{NE})[\beta_{NE} - \beta^*] + E(X'_S)[\beta^* - \beta_S]}_{\text{U}} \tag{2.6}$$

In the two-fold decomposition $R = Q + U$, $Q = [E(X_{NE}) - E(X_S)]'\beta^*$ is the component of the regional difference explained, and $U = E(X'_{NE})[\beta_{NE} - \beta^*] + E(X'_S)[\beta^* - \beta_S]$ is the unexplained port on ascribed to discrimination. The two-fold decomposition results will defer depending upon the β^* chosen. In our analysis we chose$\beta^* = \beta_S$. We also discuss findings of the the two fold decomposition using β^* estimated from the pooled regression.

2.4 Results

Preliminary tests

Preliminary tests are necessary before decomposing the differences in the mean health outcomes. For the Blinder-Oaxaca decomposition to be meaningful, it is essential that most of health outcomes and other factors to be significantly different across the two regions. Table 2.2 summarizes the tests of the mean differences in health outcomes between the two regions.

Table 2.2, third column, presents the standard *Student's t-test* of the difference in the means between the two regions. The health outcomes and health factor variables are significantly different in the two regions if the p-value of the difference in means is less than 0.1% (α). The results clearly show that all these variables are significantly different across the two regions, due to the multiple testing procedures, the confidence intervals may be inflated and the probability that the regional means differ will fall [the probability that at least of the 22 null hypothesis test is rejected when true is $1-(1-\alpha)^{22}$] . To reduce the False Discovery Rate (FDR), at a level lower than that of the uncorrected *Student's t-test p-value*, we use the Simes (1986) multiple tests procedure to estimate the minimum rates that our discovery is false (*q-value*) for each statistic. The *q-values*, in the last column of Table 2.2, close to zero confirm that the mean health outcomes and health factors differ in the northeastern and the southern counties. We can now proceed to estimate various regression models and investigate whether there is a proportion of the mean health outcome difference between the two regions that is not explained by the preferred model.

Table 2.2: Student T-test and Simes Multiple Tests of the Differences in Means

Focus Area	*Variables*	*Regional Differences*	*Q-value (dof=2346)*
Health Outcome	Premature Death	-3236.5^{***}	0
	Physical Unhealthy Days	-0.727^{***}	3.21E-94
	Mentally Unhealthy Days	-0.295^{***}	5.81E-13
	Low Birth Weight	-1.980^{***}	1.88E-202
Health Behavior	Obese	-3.997^{***}	5.26E-132
	Teenbirth	-35.28^{***}	0
Access to Care	Uninsured	-9.192^{***}	0
	PCP	37.38^{***}	4.72E-53
	MHP	64.39^{***}	0
Quality of Care	ACSC	-21.97^{***}	1.36E-58
	HBA1C	4.667^{***}	7.53E-63
Socioeconomic Factors	AFGR	7.894^{***}	6.49E-70
	Unemployed	-1.025^{***}	1.82E-13
	Singleparent	-4.257^{***}	9.78E-09
Environment	Pm days	0.391^{**}	0.746765
	Ozone days	3.008^{***}	1.25E-60
Demographics	Less18	-2.728^{***}	3.81E-128
	Over65	0.322^{*}	1.81E-05
	Black	-12.11^{***}	7.32E-98
	Hispanic	-5.952^{***}	1.43E-14
	Female	0.285^{**}	0.015296
	Rural	-17.24^{***}	5.44E-27

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Estimation results

Table 2.3 presents the regressions for decomposing the health outcomes. Across these, the significant regional dummy suggests the need for region-specific estimates. There were no major improvements when we considered state fixed effects models (See, Appendix B to Appendix E).

Table 2.3: Health Outcomes Estimation Results

	$YPPL_{75}$		PUD		MUD		LBW	
	NE	South	NE	South	NE	South	NE	South
Constant	187.6^{***}	98.60^{***}	110.7^{***}	74.04^{***}	140.9^{***}	57.84^{**}	39.67^{*}	9.238
	(-10.28)	(-7.23)	(-4.82)	(-4.05)	(-5.63)	(-2.69)	(-2.36)	(-0.95)
Obese	0.0213^{***}	0.0198^{***}	0.0110^{***}	0.0167^{***}	0.0112^{***}	0.0146^{***}	0.00857^{***}	0.00668^{***}
	(-13.4)	(-15.99)	(-5.43)	(-10.41)	(-5.05)	(-7.81)	(-5.48)	(-7.93)
Teenbirth							0.00216^{***}	0.00177^{***}
							(-4.14)	(-10.43)
Uninsured	-0.00804^{***}	-0.00449^{***}	-0.00452^{**}	-0.00622^{***}	-0.00899^{***}	-0.00428^{**}	-0.00345^{*}	-0.00372^{***}
	(-6.25)	(-5.27)	(-2.65)	(-4.92)	(-3.67)	(-2.63)	(-2.39)	(-6.23)
PCP	0.0000506	0.0000845	-0.000317^{***}	-0.000554^{***}	-0.000459^{***}	-0.000638^{***}	-0.000244^{***}	0.000141^{*}
	(-0.41)	(-1.04)	(-3.36)	(-5.72)	(-3.81)	(-4.71)	(-3.82)	(-2.29)
MHP	-0.0000964^{***}	-0.00106^{***}			-0.0000616^{*}	0.0000459		
	(-9.40)	(-4.89)			(-2.10)	(-0.13)		
ACSC	0.00204^{***}	0.00112^{***}	0.00229^{***}	0.000723^{***}				
	(-7.04)	(-11.05)	(-4.41)	(-3.98)				
HBA1C	-0.00331^{***}	-0.00328^{***}						
	(-2.59)	(-7.12)						
AFGR	-0.00190^{**}	-0.00177^{***}	-0.00272^{***}	-0.00124^{**}	-0.00210^{*}	-0.00245^{***}	0.00013	-0.000946^{***}
	(-2.98)	(-5.09)	(-3.60)	(-2.73)	(-2.25)	(-4.48)	(-0.22)	(-3.85)
Unemployed	0.0131^{***}	0.00177	0.000249	0.0113^{***}	0.00082	0.00909***	0.00517	0.0000645
	(-3.85)	(-1.38)	(-0.05)	(-6.1)	(-0.13)	(-4.17)	(-1.44)	(-0.06)
Singleparent	0.00421^{***}	0.00288^{***}	0.00537^{***}	0.00145^{*}	0.00622^{***}	0.00116	0.000718	0.00128^{***}
	(-5.61)	(-7.01)	(-4.82)	(-2.38)	(-5.42)	(-1.6)	(-1.11)	(-4.16)
Pm-days						0.00140^{**}	0.000838	
						(2.64)	(1.25)	
Ozone-days	0.00142	-0.00342^{***}	0.00150	-0.00287^{***}	0.00367^{**}	-0.000901		
	(1.50)	(-5.10)	(1.40)	(-4.66)	(2.64)	(-1.32)		
Less18							-0.00962^{***}	-0.00653^{***}
							(-4.49)	(-6.61)
Over65	0.0218^{***}	0.00762^{***}	0.00712^{**}	0.00475^{***}	0.0116^{***}	0.00445^{**}		
	(-12.23)	(-8.35)	(-2.74)	(-3.72)	(-3.94)	(-3.01)		
Female	0.0125^{***}	-0.0000765	0.0149^{*}	-0.0015	-0.00726	0.00314	0.00465	0.00845^{***}
	(-3.54)	(-0.04)	(-2.56)	(-0.69)	(-0.93)	(-1.16)	(-0.91)	(-7.55)
Rural	0.00143^{***}	0.000214	0.000291	0.000476^{*}	-0.000151	-0.000671^{**}	-0.00138^{***}	0.000565^{***}
	(-6.55)	(-1.53)	(-0.95)	(-2.42)	(-0.40)	(-2.75)	(-5.94)	(-5.54)
Hispanic	0.0000135	-0.000985^{***}	0.00402^{***}	-0.000369	0.000457	-0.00216^{***}	0.00207^{*}	0.000703^{*}
	(-0.01)	(-3.46)	(-4.24)	(-0.93)	(-0.36)	(-3.85)	(-2.41)	(-3.06)
Black	0.00741^{***}	0.000686^{**}	-0.00408^{***}	-0.00402^{***}	-0.00168	-0.00448^{***}	0.00695^{***}	0.00647^{***}
	(-8.44)	(-2.82)	(-5.34)	(-11.16)	(-1.59)	(-10.12)	(-11.12)	(-33.92)
Year	-0.0897^{***}	-0.0447^{***}	-0.0550^{***}	-0.0363^{***}	-0.0694^{***}	-0.0283^{**}	-0.0189^{*}	-0.00381
	(-9.89)	(-6.58)	(-4.82)	(-3.99)	(-5.58)	(-2.64)	(-2.27)	(-0.79)
N	706	3085	696	2847	696	2864	698	3090
R^2	0.738	0.503	0.337	0.219	0.232	0.103	0.589	0.65
$Adj-R^2$	0.732	0.5	0.322	0.215	0.216	0.099	0.581	0.648

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *T-statistics in parentheses*

$YPLL_{75}$: Premature death rate before age 75; LBW: Low Birth Weight rates

PUD: Mean Physically Unhealthy days per month; MUD: Mean Mentally Unhealthy days per month

Premature deaths

A one percent rise in obesity rates significantly increases premature death rates 2% in both regions. That is a total increase 131 Life-Years Loss per 1,000 in the northeast and 196 in the south. Moreover, obesity rates contribute most to the total Life-Years Loss in both regions. Similarly, an increase in preventable hospitalization for Medicare enrollees (ACSC) increases the number of Life-Years Loss. A percentage point rise in the number of avoidable hospitalizations increases the total number of Life-Years Loss by 13.5 and 11 years respectively in the northeast and in the south. Prevention (diabetes screening, HBA1C) significantly reduces the number of Life-Years Loss, e.g., a 10 percent point increase in the number of diabetic Medicare enrollees who receive HbA1c screening reduces premature death rates by 3% across the two regions.

Most socioeconomic factors have the expected effects and the coefficients are marginally significant. The more educated a county's population is the less the premature death rate. An increase of the Average Freshman Graduation Rate (AFGR) by 1% reduces premature death rates by approximately 0.2%. As expected, the unemployed are more likely to die prematurely; in the northeast, a percentage rise in the unemployment rate leads to 1.3% rise in the number of Life-Years Loss, but unemployment rate does not have a discernible effect in the south. Lastly, family structure is important in population well-being: a percent rise in single-parent household increases number of Life-Years Loss by 26 years in the northeast and 39 years in the south.

As expected, death in later years accounts for some Life-Years Loss in both regions, which justifies the need to consider relative death rates in place of crude mortality rates. In the northeast, a point increase of the female percentage significantly raises the number of life-years loss, and a percentage point increase in the rural population increases the premature death rates by 0.14%. However, these variables do not have significant effect on premature death rates in the south. A one percent rise in the black population in both regions increases premature death rates by 0.7% in each region. Ethnic minorities have lower education, earn less and have lower health status. Interestingly, we find the Hispanic population living longer in the south. Our estimation results are in accordance with previous findings. For example, Schroeder (2007) concludes that of the 5 major causes of premature deaths (genetics, socio-economic factors, habits, health care factors, and environmental factor) access to health care play a significantly minor role compared to behavioral (e.g., obesity) and socio-economic factors.

Mean Physically and Mean Mentally Unhealthy Days per Month

As expected, being obese would significantly induce one to report more unhealthy days per month. In the northeast region, a percent increase in obesity rate causes 1.1% increase in the number of unhealthy days. The impact is much higher in the south; 1.67% increase in physically unhealthy days and 1.46% increase in mentally unhealthy days.

All the socio-economic factors have the expected effects on the number of unhealthy days and they are significant in most cases. The older the population, the more unhealthy days are reported during any given month. Rural residents tend to report more, statistically insignificant, physically unhealthy days, and an increase in rural population rates significantly reduce the number of reported mentally unhealthy days. This finding could be partly explained by the rural-urban differences in work structure, lifestyle, and environment. Rural workers tend to engage more in physically-demanding activities and may be less prone to urban area stress. Caution that the estimation results explain only a small portion of the reported unhealthy days, as these two measures are self-reported and may not fully capture the population health status.

Females tend to report more unhealthy days. Moriarty *et al.* (2003), on examining surveillance-based health related quality of life data between 1993 and 2002, similarly found for all ethnic groups, that women report on average one more physically and mentally unhealthy days than men. Moreover, adults older than 75 also reported a greater number of physically unhealthy days and married individuals reported, on average, less unhealthy days than never married persons and unmarried couples. Also, adults with less high school education reported more physically and mentally unhealthy days than those with high school education. In addition, adults who are unable to work or unemployed reported more physically unhealthy days and more mentally unhealthy days. Jia and Lubetkin (2005) concluded that all health related quality of life measures decreased with greater obesity level.

Low Birth Weight

Health behaviors contribute significantly to the rise in low birth weight rates. A one percentage point increase in the obesity rates increase low birth weight rates by 0.86 in the northeast and by 0.67 in the south. Similarly, a percentage point increase in the teen birth rate leads, on average, to 0.2% increase in low birth weight rates in both regions. While marginally small, an increase in the average freshman graduation rate in the south appears to reduce low birth weight rates. An increase in the number of single-parent households in the south increases low birth weight rates. Not surprisingly Table 2.3 results suggest that socio-economic factors do not play a significant role as a determinant of the low birth weight rate in the northeast.

The higher the percentage of individuals younger than 18 years, the lower the low birth weight rate. Intuitively, this could be explained by more effective prenatal interventions in recent years. The rural population percent reduces significantly low birth weight rates by 0.14% in the northeast but increases it by 0.056% in the south. As expected, all of the ethnic minority groups have relatively low birth weight outcomes. Moreover, and s expected, a rise in the percentage of uninsured adults in the population improves health outcomes as are improved access to the various health care providers.

The standardized beta coefficients (Appendix F) suggest the obesity rates to be one of the strongest predictors of health outcomes, across all measures in the two regions. Excess weight is linked to many health problems, including Type-2 diabetes, cancers, coronary heart disease, osteoarthritis, pregnancy complications, and premature mortality.

2.5 Health outcome decomposition

Using estimation results in Table 2.3, we decomposed the regional differences in mean health outcomes. Our goal is to find out if the difference in health outcomes across the two regions could be driven by some unmeasured factors. Two types of decompositions are presented: a three-fold decomposition (endowment, coefficient and interaction effects) in Table 2.4 and a two-fold decomposition (explained and unexplained components) in Table 3.5[6] .

6. In the two-fold decompositions, betas from the Southern States counties were considered.

The first panel of Tables 2.4 and Table 2.5 reports each region's health outcomes logarithmic predictions, and the regional difference.

Table 2.4: Three-Fold Decompositions

	$YPLL_{75}$	*MUD*	*PUD*	*LBW*
Northeast	8.774***	1.230***	1.223***	1.989***
	(1190.94)	(191.04)	(175.76)	(357.54)
South	9.169***	1.408***	1.287***	2.219***
	(2323.45)	(316.79)	(251.90)	(613.56)
Difference	-0.395***	-0.178***	-0.0636***	-0.230***
	(-47.22)	(-22.69)	(-7.36)	(-34.65)
Endowment Effect	-0.190***	-0.0434***	-0.0044	-0.141***
	(-11.50)	(-3.78)	(-0.19)	(-18.28)
Coefficient Effect	-0.163***	-0.104***	-0.0591**	-0.0827***
	(-11.40)	(-5.55)	(-2.77)	(-4.90)
Interaction Effect	-0.0420*	-0.0298	-7.8E-05	-0.00663
	(-2.04)	(-1.44)	(-0.00)	(-0.37)
N	3791	3543	3560	3788

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *t-Statistics in parentheses*

Table 2.5: Two-Fold Decompositions

	$YPLL_{75}$	*MUD*	*PUD*	*LBW*
Northeast	8.774***	1.230***	1.223***	1.989***
	(1194.43)	(195.00)	(178.72)	(350.25)
South	9.169***	1.408***	1.287***	2.219***
	(2295.10)	(309.56)	(256.37)	(612.63)
Difference	-0.395***	-0.178***	-0.0636***	-0.230***
	(-47.20)	(-22.83)	(-7.49)	(-34.13)
Explained Portion	-0.232***	-0.0732***	-0.00448	-0.147***
	(-13.60)	(-4.72)	(-0.23)	(-9.22)
Unexplained Portion	-0.163***	-0.104***	-0.0591**	-0.0827***
	(-9.67)	(-5.99)	(-2.60)	(-5.16)
N	3791	3543	3560	3788

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$*; t-Statistics in parentheses*

Premature deaths

The premature death rate decompositions predict an average 6464 ($= e^{8.774}$) Life-Years Loss per 100,000 for the northeastern counties, and 9595 ($= e^{9.169}$) in the southern counties. The model predicts premature death rates to be 39.5% higher in the south.

The three-fold decomposition results in Table 2.4, first, indicate that about 48.1% of the regional difference in the premature death rates is explained by each region's endowments in health factors. Intuitively, it implies that the number of Life-Years Loss in the northeast would have been lower by 1506 years per 100,000, if the northeastern counties had the same health characteristics as the southern counties. Second, the coefficient effect indicates that approximately 4.26% of that difference is explained by the regions' coefficients, that is if the regression coefficients from southern counties were applied to the northeastern counties, the number of Life-Years Loss would have been lessen by 1292 years. Lastly, the interaction term which accounts for the difference in coefficient and endowments occur simultaneously represent only 10.63% of the difference. The two-fold decomposition suggests that 58.73% ($= \frac{0.232}{0.395}$) of the regional difference is explained by the model, while 49.26% ($= \frac{0.163}{0.395}$) remains unexplained.

Mean unhealthy days per month

On average, the models predict for the northeastern counties that an adult reports 3.4 ($= e^{1.23}$) physically unhealthy days, and 3.4 ($= e^{1.223}$) mentally unhealthy days per month. It also predicts 4.09 ($= e^{1.408}$) physically unhealthy days, and 33.62 ($= e^{1.287}$) mentally unhealthy days per month for the southern counties. The decomposition suggests that, in the south, the average physically unhealthy days are 17.8% higher and the mean mentally unhealthy days, 6.36% higher than those in the northeast. These estimates, *a-priori*, may appear marginally small, however if aggregated for the entire workforce and expressed monetarily, represents a substantial loss in social welfare.

The three-fold decomposition, for both outcomes, indicates that most of the regional difference is caused by the coefficient effect: the average number on physically unhealthy days per month in the northeast would be 58.42% lower if the southern counties coefficient estimates were applied; and the average mentally unhealthy days per month 93% lower. Only 24.38% of the difference in physically unhealthy days and 7% of the difference in mentally unhealthy days between the two regions was explained by the regions health endowments.

The two-fold decompositions indicate that, respectively, 76.4% and 88.68% of the regional differences in physically and mentally unhealthy days per month are not explained by the regression models.

Low birth Weight

The low birth weight decompositions predict an average low birth weight rate of 7.31% for the northeastern counties and 9.2% for the southern counties, yielding a regional difference of 1.89 percentage point, a 23% regional difference. The three-fold decomposition result suggests 61.30% of this difference to be explained by the regions' endowments in health factors: if the northeastern counties had identical health endowments to the southern counties, out of 100 live births, 6 more infants would weigh less than 2500g. The coefficient effect indicates that about 35.95% of the difference is explained by the regions coefficients, meaning that if the northeastern counties had the same coefficient as the southern counties, the premature deaths rates would have been of 12.5% instead of 7.31%. Finally, the interaction term which accounts for the fact that the difference in coefficient and in endowments occur simultaneously represent 3% of the overall difference in low birth weight rate between the two regions.

The two fold decomposition indicates that 61.74% of the regional difference is explained by the selected regressions.

Comparable results obtained when, instead of using betas from the south as reference in the two-fold decompositions, regressors from a pooled model were used. (See, Appendix G).

2.6 Conclusion

This study investigates whether regional disparities could partially explain differences in the population health outcomes, variously measured, in southern and northeastern US states.
Using a 3-year county level data in these states, we were able to separate the proportion of the difference in health outcomes in these regions (northeast and the south) into that explained by the regions' health endowments and the proportion unexplained (e.g., regional health disparities). We considered four relevant health outcomes that include mortality measure (potential number of Life-Years loss before age 75) and three morbidity measures (mean physically and mean mentally unhealthy days per month; and low birth weight rate). Two of the health outcomes measures are *self-accessed* (mean unhealthy days), thus we anticipated that the policy inferences would differ from those of the more objective, *clinically-accessed*, measures (As in, Chen *et al.*, 2010).

The best fitted regression for each health outcome was used for conducting the Blinder-Oaxaca decomposition. For all regressions, obesity rate and access to care determinants impact strongly on each region's health outcomes. Our results also suggest that an important proportion of the difference in health outcomes between the two regions has yet to be explained when using the more objective health outcome measures. We find approximately half of the difference in premature death rates and in low birth weight rates to be unexplained by the regions health endowments.

Some policy implications arise from these findings. First, the relatively high proportion of the regional difference in the *clinically-accessed* health outcomes not explained by regional health factors suggests the prevalence of regional discrimination in health outcomes. Second, in order to raise US population health status, it is important to focus on region-specific preventive care. Third, more effective public education and information strategies raising population awareness to the health dangers of obesity are in order. Fourth, broad-based access to various health services personnel should be provided to populations (Kennedy, 2005). Regarding insurance coverage, the reforms inspired by countries with more effective healthcare systems could reduce disparities in health outcomes among US regions. Finally, our research findings echo the McGinnis *et al.*, (2002) recommendation that future US health strategies and policies should target more of the "actionable determinants" of health (behavioral factor, access to care, income, and education) in the region with atrophied health status. Additionally, more effective incentives to attract healthcare providers to the currently under-served zones (e.g., through tax-credits and student loan abatements) on a sustainable basis could raise access to care in low performing US regions, e.g., the south.

Future studies might look further into the impact of regional disparities on health status, beyond the behavioral, access to care, socio economic and demographic factors. For example what could be the impact of a region's overall stress level on its population resistance to illnesses?

CHAPTER 3

SUBSTITUTABILITY, COMPLEMENTARY, AND RISK WITH STRATEGIC INTERACTIONS: AN APPLICATION TO GLOBAL WARMING

3.1 Introduction

This paper addresses a policy issue that raises some interesting theoretical questions.The policy issue is about how uncertainty about climate change affects global emissions of greenhouse gases. The fourth assessment of the Intergovernmental Panel on Climate Change (IPCC, 2007) concluded that the earth's climate is changing, and that these changes can be attributed to the increase in atmospheric greenhouse gas concentration. However, the science of climate change is so complex that there is inescapable uncertainty about both the sources and the consequences of climate change. The IPCC report emphasized the importance of recognizing these uncertainties, but they elicit widely divergent reactions. On the one hand, some(*for example*, Seitz, 1994) contend that climate change is not a serious threat to humankind. On the other hand, others (*for example*, Andronova, Schlesinger, & Yohe, 2004) argue that it would be prudent to pursue policies that reduce greenhouse gases emissions, precisely because of the uncertainties inherent in climate change science. Even if such policies are desirable, however, implementing them may be problematic: each country may have even incentive to "free ride," and let other countries carry the burden of reducing emissions.

The theoretical challenge is to construct a model that incorporates both uncertainty about climate change and strategic behavior, in order to investigate how an economic agent emission level and welfare will be affected by greater climatic risks. When should the world as a whole reduce its emissions of greenhouse gases? How do strategic interactions complicate the achievement of this goal? Is it possible that uncertainty can, by inducing a prudent reduction in emissions, at least partially offset the sub-optimality caused by free-riding behavior? As Bramoullé and Treich (2009) put it in the provocative title of their recent paper, *"Can Uncertainty Allevi-*

ate the Commons Problem?" Their answer is a tentative yes: Uncertainty about environmental quality may actually increase welfare, if the positive effect of reducing their emissions is higher than the negative effect of uncertainty.

In this paper we generalize the model of Bramoullé and Treich (2009) [*hereafter* B&T] to investigate these questions in a richer environment and to see how robust their conclusion remains. They imagine a world comprised of n countries, where each country i derives utility from the environmental quality q, and its emissions e_i. Environmental quality depends upon aggregate emissions of all of the countries, and is subject to a random shock. Their utility function is very special: $U(e_i,q) = u(e_i + q)$, where u is increasing and concave, $u' > 0, u'' < 0$. This amounts to assuming that the country is risk averse with respect to the *linear* aggregator $e_i + q$ so that (in the absence of uncertainty) the country would view emissions and environmental quality as perfect substitutes. This, requires emissions and environmental to be Edgeworth complements (since $U_{eq} = u'' < 0$), which in turn forces countries' emissions to be *strategic* substitutes (Bulow, Geanakoplos, & Klemperer, 1985).

In this paper we employ a general function $U(e_i,q)$. The only restriction we impose on this function is concavity. This has two important consequences. First, it allows a much richer characterization of risk preferences: Given concavity, the country is risk averse with respect to both arguments($U_{ee}, U_{qq} < 0$). However, we allow emissions to be either Edgeworth substitutes or complements. The country may thus be either *correlation-averse* ($U_{eq} \leq 0$) or *correlation-loving* ($U_{eq} \geq 0$) (Eeckhoudt, Ray, & Schlesinger, 2007). Furthermore, the country may be *prudent* ($U_{eee} > 0$) or *imprudent* ($U_{qqq} < 0$) (the terminology is adapted from Kimball,1990); it may be *cross-prudent environmental quality* ($U_{eqq} \geq 0$) or *cross-imprudent* ($U_{eqq} \leq 0$) in environmental quality (see again Eeckhoudt, Ray, & Schlesinger, 2007). These risk preferences interact in a complicated way to determine the *direction* of the country's response to an increase in environmental uncertainty. Allowing emissions and environmental quality to be Edgeworth complements within countries, also permits these countries' emissions to be strategic substitutes. Second, whether emissions are strategic substitutes $-$ as they are in extreme form in B&T$-$ or strategic complements will determine the *magnitude* of the response to risk. This is because strategic complementarity induces well-known "multiplier" effects.

Our model is a descendant of the seminal paper by Gradstein, Nitzan, and Slutsky (1990) on Nash equilibrium with uncertainty. Unlike them, however, we prove the existence of a unique equilibrium rather than assume it. This in turn provides a condition that allows us to determine the sign of the effect of uncertainty on emissions. Our purpose is also different from theirs. They establish conditions under which the direction of the effect of uncertainty on the choice variables is the same in the Nash equilibrium as for an individual decision maker. Our purpose is to determine conditions under which uncertainty will reduce emissions and by how much and hence, possibly, improve welfare.

The outline of the paper is as follows. Section 2 describes the model. Section 3 characterizes the socially optimal emissions set by a social planner and establishes the existence of a unique Nash equilibrium in the strategic setting. Section 4 determines the conditions under which an increase in uncertainty about environmental damages will reduce greenhouse emissions. Section 5 considers when uncertainty will actually improve welfare. Section 6 offers some concluding thoughts.

3.2 Model

Our model is an extension of that of B&T. There are $n \geq 2$ countries, of which each country$i = 1, \ldots, n$ engages in emissions $e_i \geq 0$.

Technology

Each country$i = 1, \ldots, n$ engages in emissions $e_i \geq 0$. A country enjoys benefits from emitting, but by doing so contributes the degradation of environmental quality. Following of B&T, we assume that the benefit of emitting is simply equal to the rate of emissions itself (e.g, greater emissions increase the prodruction level).

Environmental quality q depends upon the total emissions of all of the countries $\sum_{i=1}^{n} e_i$, according to the production function

$$q = \bar{q} - \theta d(\sum_{i=1}^{n} e_i) \tag{3.1}$$

$\bar{q}$ is the maximum environmental quality level attainable, a pristine environment. The function $d(\sum_{i=1}^{n} e_i)$ is the damage function. It is increasing and convex in total emissions, so $d' > 0, d'' \geq 0$. Furthermore, no environmental degradation occurs when there are no emissions, so $d(0) = 0$. The damage caused by emissions is uncertain: damage in each country is subject to a multiplicative shock θ_i, assumed to be non-negative. Since the shocks are assumed to be identical *ex ante*, we will henceforth write $\theta_i = \theta$. This specification of technology is identical to that of B&T except that we incorporate the endowment of environmental quality $\bar{q}$.

Preferences

Each country i derives utility from both its emissions and the quality of the environment according to the utility function $U(e_i, q)$. In contrast to B&T we impose no restrictions on this utility function other than that it be increasing and concave in both arguments. We assume that all countries share the same preferences.

Concavity requires risk aversion with respect to both emissions and environmental quality, $U_{ee} < 0, U_{qq} < 0$. However, the cross-partial partial U_{eq} will also play an important role in our analysis. Marginal utility is *super-modular* if $U_{eq} > 0$ and *sub-modular* if $U_{eq} < 0$[1] . *Sub- or super-modularity* affects behavior in two distinct ways.On the one hand, in a world without uncertainty the sign of U_{eq} governs whether emissions and environmental quality are Edgeworth complements ($U_{eq} > 0$) or substitutes ($U_{eq} < 0$). Since an increase in emissions by another country reduces environmental quality, Edgeworth complementarity is a sufficient condition for emissions in different countries to be *strategic substitutes* (Bulow, Geanakoplos, & Klemperer, 1985) −in other words, the reaction functions will be negatively sloped and the game will be sub-modular [Amir, (2005)]. If, however, emissions and environmental quality are sufficiently strong Edgeworth substitutes then it is possible for emissions in different countries to be strategic complements, so the game will be super-modular.

1. See the excellent survey on super-modularity by Amir (2005).

It is important in this regard to notice how restrictive the utility function used by Bramoullé and Treich (2009) is. If $U(e_i, q) = u(e_i + q)$, as they assume, then because of diminishing marginal utility emissions and environmental quality must be Edgeworth complements, $U_{eq} = u'' < 0$. This precludes the possibility of strategic complementarity. Their utility function is a concave transformation of the *linear* aggregator $e_i + q$, so they in effect assuming ordinal preferences between emissions and environmental quality are perfect substitutes.

On the other hand, in a world of uncertainty the sign of U_{eq} also governs whether the preferences are *correlation-averse* ($U_{eq} \leq 0$) or *correlation-loving* ($U_{eq} \geq 0$). Eeckhoudt, Ray, and Schlesinger (2007) define a person to be correlation-averse if he prefers a 50-50 gamble of a loss in his emission level or deterioration of the environment q to a 50-50 gamble loss in both or a loss in neither. Intuitively, being correlation-averse means that by enjoying the benefit of more emissions the country can reduce the pain of a reduction in environmental quality[2] . Conversely, a correlation-loving country perceives an increase in emissions as exacerbating the loss in environmental quality. Whether a country is correlation-averse or correlation-loving will be an important ingredient in how it responds to uncertainty about environmental quality. B&T implicitly confound risk aversion and correlation aversion (since $U_{ee} = U_{qq} = U_{eq} = u'' < 0$ in their formulation).

The third derivatives of the utility function will also affect how a country responds to risk. Adapting the terminology of Kimball (1990), we will say that a country is prudent with respect to emissions if $U_{eee} > 0$, and that it is prudent with respect to environmental quality if $U_{qqq} > 0$. However, a cross, third-order derivative will also play a role. Following Eeckhoudt, Ray, and Schlesinger (2007), we say that a country is *cross-prudent in environmental quality* if $U_{eqq} \geq 0$. If $U_{eqq} \leq 0$ then the country is *cross-imprudent in environmental quality*. A country that is cross prudent in environmental quality level will prefer a $50-50$ gamble of a random shock to emissions or a non-random decrease of environmental quality to a $50-50$ gamble of either keeping

2. We are paraphrasing the intuitive discussion by Eeckhoudt, Ray, and Schlesinger (2007).Formally, let $k \in [0, e]$ and $c \in [0, q]$ be two constants and denote a lottery defined over the outcomes $(\hat{e}, \hat{q})$ or $(\check{e}, \check{q})$ by $[(\hat{e}, \hat{q}), (\check{e}, \check{q})]$, where the outcomes occur with the same probability. Correlation aversion implies that $[(e_i - k, q), (e_i, q - c)] \succ [(e_i, q), (e_i - k, q - c)]$. They show that this is equivalent to $U_{eq} \leq 0$ if preferences can be represented with a utility function that is differentiable to the requisite order.

the same levels of the two attributes or facing a random shock to emissions and a non- random decrease in environmental quality. Intuitively, a higher emission level mitigates the negative impact of the environmental risk[3] . B&T implicitly confound prudence and cross-prudence (since $U_{eee} = U_{qqq} = U_{eqq} = u''' < 0$ in their formulation).

3.3 Equilibria

We will consider both the emissions that would be chosen by a welfare-maximizing social planner and the emissions determined in a Nash equilibrium.

The Social Planner

We again follow B&T, and assume that social welfare is simply the sum of the utilities of all of the countries. Since preferences are identical we will focus, as they do, on a symmetric profile $e_i = e, \forall\, i$. The welfare metric is then simply:

$$W(e) = E_\theta U[e, \bar{q} - \theta d(ne)] \tag{3.2}$$

A social planner maximizes welfare by equating the expected marginal benefits of emissions with the expected marginal social costs. He therefore chooses emissions e^W such that:

$$E_\theta \varphi(e^W, \theta) = E_\theta U_e[e^W, \bar{q} - \theta d(ne^W)] - n\theta d'(ne^W) U_q[e^W, \bar{q} - \theta d(ne^W)] = 0. \tag{3.3}$$

3. We again are expressing the discussion of Eeckhoudt, Ray, and Schlesinger (2007) in terms of the two goods in our model. Formally, consider the same loss in the benefit argument $k \in [0, e]$ or in environmental quality $c \in [0, q]$ and now imagine random shock $\tilde{\theta}$ to emissions. Cross prudence in environmental quality, written in lottery form, implies that $[(e_i, q + \tilde{\theta}), (e_i - k, q)] \succ [(e_i, q)(e_i - k, q + \tilde{\theta})]$. They show that if preferences can be expressed with a utility function that has up to third-order derivatives then this is equivalent to $U_{eqq} \geq 0$ for all e and q.

Notice that expected marginal costs are weighted by the number of countries, n. For future reference we note the second-order condition for the planner's problem,

$$E_\theta \varphi_e(e,\theta) = E_\theta[U_{ee} - 2n\theta d' U_{eq} + \theta^2 n^2 (d')^2 U_{qq} - \theta d'' U_q] < 0. \tag{3.4}$$

Concavity of $U(e,q)$ and convexity of $d(ne)$ guarantee that this is satisfied. Denote the socially optimal level of emissions by e^W.

Nash equilibrium

Now suppose that countries play a smooth game in emissions. For simplicity we focus on a symmetric game, since asymmetric behavior is not crucial to the problem of the commons. Each country chooses its emissions to maximize its expected utility, given the emissions of the other countries. It does so by emitting up to the point where the marginal benefit of emitting, $E_\theta U_e^i(e_i,q)$, is equal the expected private marginal cost $E_\theta \theta d' U_q^i(e_i,q)$. This yields the first-order conditions:

$$E_\theta \phi^i(e^N,\theta) = E_\theta[U_e^i(e_i,q) - \theta d' U_q^i(e_i,q)] = 0 \qquad i = 1,\ldots,n \tag{3.5}$$

The Nash equilibrium consists of a vector of emissions $e^N = (e_1^N, e_2^N, \ldots, e_n^N)$ that satisfies this system of equations. The second-order condition for each country's problem is:

$$E_\theta \phi_{e_i}^i = E_\theta[U_{ee}^i - 2\theta d' U_{eq}^i + \theta^2 (d')^2 U_{qq}^i - \theta d'' U_q^i] < 0 \qquad i = 1,2,\ldots,n \tag{3.6}$$

where the arguments of the derivatives are the same as in Equation (3.5).

To prove existence and uniqueness we apply the Gale-Nikaido (1965) theorem[4] . We relegate the details of the derivation to Appendix H, but will need to discuss elements of it here in order to exposit arguments that will follow later in the paper.

First, define

$$\alpha_i = E_\theta[U^i_{ee} - \theta d' U^i_{eq}] \tag{3.7}$$

$$\beta_i = E_\theta[-\theta d' U^i_{eq} - \theta d'' U^i_q + (\theta d')^2 U^i_{qq}] \tag{3.8}$$

The Jacobian J of the system of Equations (3.5) can then be expressed as

$$J = \begin{pmatrix} \alpha_1 + \beta_1 & \beta_1 & \cdots & \beta_1 \\ \beta_2 & \alpha_2 + \beta_2 & \cdots & \beta_2 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_n & \beta n & \cdots & \alpha_n + \beta_n \end{pmatrix} \tag{3.9}$$

The diagonal elements of the Jacobian register the effects of each country i's own emissions on its net marginal benefits; $\alpha_i + \beta_i = E_\theta \phi^i_{e_i} < 0$ by the by the second-order conditions of each country's maximization problem [this corresponds to the second-order condition for the planner in inequality (3.4)].

4. See the lucid discussion in Friedman (1990), as well as the succinct statement of the theorem in Sydsæter, Strøm, & Berck, 2005.

The off-diagonal elements $\beta_i = \phi^i_j, j \neq i$, capture the effects of the emissions of other countries on the net marginal benefits of country i; if $\beta_i < 0$, emissions in other countries are strategic substitutes for those of country i, while if $\beta_i > 0$ they are strategic complements. Notice that $U^i_{eq} > 0$ (super-modularity) is a sufficient condition for strategic substitutability. However, if U^i_{eq} is sufficiently negative it is possible for emissions to be strategic complements.

Since preferences are identical, an interior equilibrium must necessarily be symmetric, so that $\alpha_i = \alpha$ and $\beta_i = \beta$. In the Appendix H we prove

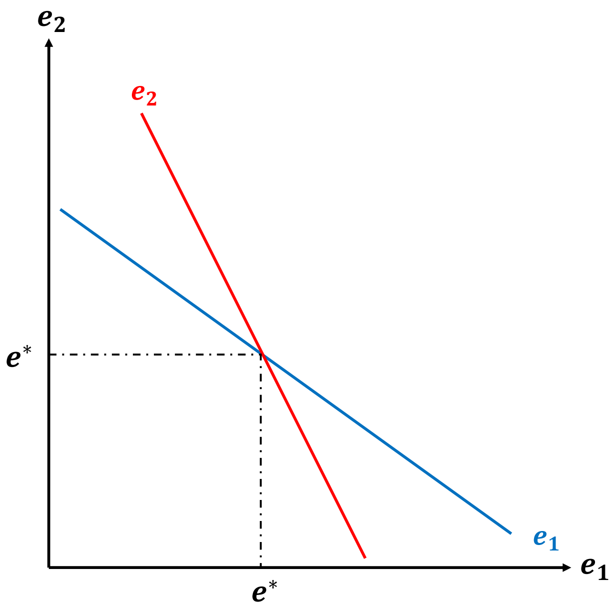
Proposition 1 *There exists a unique, interior, symmetric Nash equilibrium $e^N = (e^N_1, e^N_2, \ldots, e^N_n)$ if $\alpha^{j-1}[\alpha + j\beta]$ alternates in sign negative, positive, negative,..., for $j = 1, 2, \ldots, n$. Further, these conditions will be satisfied if and only if $\alpha < 0$ and $\alpha + j\beta < 0$.*

A sufficient condition for $\alpha < 0$ [*see* Equation (3.7)] is that, for every realization of θ, emissions and environmental quality are complements ($U_{eq} > 0$). The restriction $\alpha + j\beta < 0$ is satisfied automatically if emissions are strategic substitutes ($\beta < 0$). However, strategic complementarity ($\beta > 0$) is consistent with equilibrium as long as the strength of complementarity is not too strong. A sufficient condition for $\alpha + j\beta < 0$ [*see* Equation (3.8)] is that, for every realization of θ, the restriction that

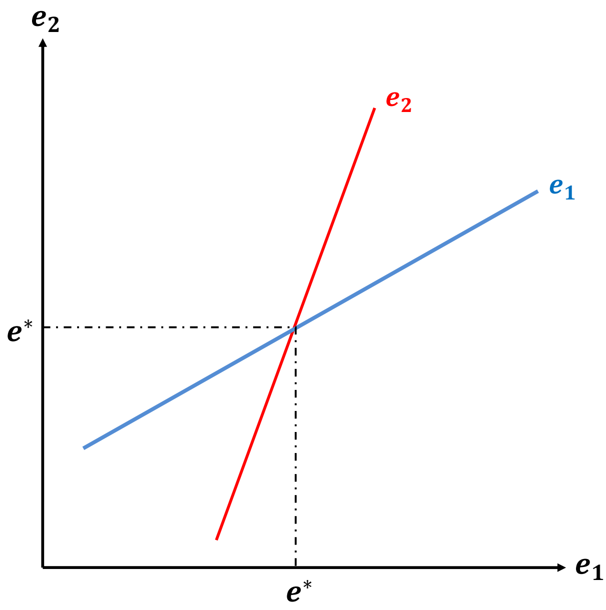
$$U_{ee} - \theta d' U_{eq} + j[-\theta d' U^i_{eq} - \theta d'' U^i_q + (\theta d')^2 U^i_{qq}] < 0. \tag{3.10}$$

In other words, there will be a unique equilibrium as long as emissions are either super-modular or not too strongly sub-modular.

In the two-dimensional case, Proposition 1 has an illuminating geometric interpretation. Suppose that there are two countries, 1 and 2. Proposition 1 then asserts that there is a unique equilibrium if $\alpha + \beta < 0$ and $\alpha(\alpha + 2\beta) > 0$. The first inequality follows from the second-order condition for each country. To see what the second inequality means, consider the slopes of the reaction functions for the two countries: $\left.\frac{de_2}{de_1}\right|_1 = -\frac{\alpha+\beta}{\beta}$ and $\left.\frac{de_2}{de_1}\right|_2 = -\frac{\beta}{\alpha+\beta}$. The condition $\alpha(\alpha+2\beta) > 0$ simply requires one reaction function to be steeper than the other. Notice that if $\beta > 0$ the reaction functions are positively sloped (*See* Figure 3.1).



(a) Strategic Substitutes, $\frac{de_2}{de_1} < 0$



(b) Strategic Complements, $\frac{de_2}{de_1} > 0$

Figure 3.1: Reaction Functions.

We pause to establish an obvious but important result. Since the equilibrium is symmetric we can write $U^i = U$ and reduce the system in Equation (3.5) to the single equation

$$E_\theta \phi(e^N, \theta) = E_\theta U_e[e^N, \bar{q} - \theta d(ne^N)] - \theta d'(ne^N) U_q[e^N, \bar{q} - \theta d(ne^N)] = 0. \tag{3.11}$$

Each country equates the expected marginal benefit of emissions to the expected *private* costs. This should be compared to the first-order condition of the planner, in Equation (3.3), where the expected marginal social costs are proportional to the number of countries, n. We can then infer

Proposition 2 *Emissions in the Nash equilibrium always exceed the socially optimal rate of emissions,* $e^N > e^W$.

This of course also holds in Bramoullé and Treich (2009).

3.4 Emissions and Uncertainty

Should uncertainty about the environmental damages of emissions lead countries to pollute less? How does such uncertainty affect the rate of emissions when countries act strategically? To address these questions we will consider the effects of an increase in risk, in the sense of Rothschild and Stiglitz (1970), on the socially optimal rate of emissions and in the Nash equilibrium.

Uncertainty and the social planner

To be precise, suppose that the distribution of θ is initially $g(\theta)$ and denote the socially optimal emissions associated with that distribution by e_g^W. Let the distribution of θ change to $h(\theta)$, where $h(\theta)$ is a mean-preserving spread of $g(\theta)$. Denote the socially optimal emissions associated with $g(\theta)$ by e_h^W. We are interested in whether the increase in risk commands a decrease in emissions: When is $e_h^W < e_g^W$?

Initially, given $g(\theta)$, the planner chooses emissions so that $E_\theta \varphi(e_g^W, \theta) = 0$. Intuitively, we know from standard arguments of stochastic dominance that the mean-preserving spread will decrease $\varphi(e,\theta)$ if $\varphi(e,\theta)$ is concave in θ, so that $E_\theta \varphi(e_g^W, \theta) < 0$. If $\varphi(e,\theta)$ is decreasing in e then to regain $E_\theta \varphi(e_h^W, \theta) = 0$ the planner must reduce emissions, so that $e_h^W < e_g^W$. Adapting the elegant formulation of Gradstein, Nitzan, and Slutsky (1992), we can say more generally that

$$Sign(e_g^W - e_h^W) = Sign(\varphi_{\theta\theta}) \times Sign(\varphi_e) \tag{3.12}$$

We know that $\varphi_e < 0$ from the second-order condition in inequality (3.4). The question therefore reduces to assessing the sign of $\varphi_{\theta\theta}$.

A little algebra reveals that

$$\varphi_{\theta\theta} = d^2[U_{eqq} - n\theta d' U_{qqq} + 2n\frac{d'}{d}U_{qq}] \tag{3.13}$$

Following Dardanoni (1988) this expression can usefully be decomposed into two parts.

- The second terms in brackets corresponds to what Dardanoni (1988) calls the "uncertainty substitution effect." This is negative, assuming that people are risk-averse with respect environmental quality, $U_{qq} < 0$. Risk aversion unambiguously makes socially optimal emissions fall when uncertainty increases.

- The first two terms inside the bracket constitute what he dubs the "uncertainty income effect." This in turn depends upon two factors, U_{qqq} and U_{eqq}. If people are prudent $U_{qqq} \geq 0$ then the effect of risk aversion is reinforced. However, if people are cross-prudent $U_{eqq} \geq 0$ with respect to environmental quality then an increase uncertainty tends to raise the marginal utility of emissions.

This leads to:

Proposition 3 *An increase in uncertainty about the environmental damages of emissions will increase (reduce) the socially optimal rate of emissions as* $U_{eqq} - n\theta d' U_{qqq} + 2n\frac{d'}{d}U_{qq}$ *is positive* *(negative).*

One might think that a risk-averse planner would always reduce emissions in response to environmental uncertainty. However, Proposition 3 establishes that a sufficiently cross-prudent planner might actually *increase* emissions in response to greater risk about their effect on environmental quality[5] .

To make this more concrete it may help to consider a "small" risk. Define $\theta = \bar{\theta} + \sigma\varepsilon$, where $E(\varepsilon) = 0$ and $Var(\varepsilon) = 1$, so a small σ implies a small risk to θ. Define the socially optimal rate of emissions in the absence of uncertainty ($\sigma = 0$) by $\bar{e}^W$. Taking a Taylor-series of Equation (3.3) around $e^W = \bar{e}^W$ and around $\varepsilon = 0$ then yields

$$e^W = \bar{e}^W - \frac{\varphi_{\theta\theta}}{\varphi_e}\frac{\sigma^2}{2} \tag{3.14}$$

The functions $\varphi_{\theta\theta}$ and φ_e are of course evaluated at $\sigma = 0$. Since $\varphi_e < 0$, uncertainty only reduces emissions relative to the case without uncertainty if $\varphi_{\theta\theta} < 0$, as Proposition 3 asserts. This will happen unless the country is very cross-prudent.

Uncertainty with strategic interactions

Now consider the effects of uncertainty in the Nash equilibrium. Denote the emissions in the symmetric Nash equilibrium for the less risky distribution $g(\theta)$ by e_g^N and the equilibrium emissions for the riskier distribution $h(\theta)$ by e_h^N. Recall from Equation (3.5) that the first-order condition for each country i is $E_\theta \phi^i(e^N, \theta) = 0$.

Following the same reasoning as in the previous section it follows that the sign effect of the increase in risk on equilibrium emissions is determined by

5. B&T attribute this ambiguity to prudence. This is because their preferences $U(e+q)$ impose $U_{eqq} = U_{qqq} = u'''$. In fact it is cross prudence that generates the ambiguity, if people are prudent, $U_{qqq} > 0$.

$$Sign(e_g^N - e_h^N) = Sign(\phi_{\theta\theta}) \times Sign(\phi_e) \tag{3.15}$$

This corresponds, *mutatis mutandis*, to Equation (3.3) of Gradstein, Nitzan, and Slutsky (1992). Consider the two terms on the right-hand side of (15) in turn.

Gradstein, Nitzan, and Slutsky (1992, p.557) emphasize that the derivative ϕ^i must account for the fact that *all* countries are changing their emissions, as well as country i. In other words, ϕ_e^i is the derivative of ϕ^i with respect to the common rate of emissions e^N in the symmetric equilibrium. This turns out to be

$$\phi_e^i = [U_{ee}^i - 2\theta d' U_{eq}^i + (\theta d')^2 U_{qq}^i - \theta d'' U_q^i] - (n-1)[\theta d' U_{eq}^i + \theta d'' U_q^i - (\theta d')^2 U_{qq}^i] \tag{3.16}$$

The first term is simply the second-order condition in Inequality (3.6), and so is negative. The second term is the change in country $i's$ marginal utility of emissions caused by a change in country $j's$ emissions, $\frac{\partial^2 U^i}{\partial e_i \partial e_j}$. Gradstein, Nitzan, and Slutsky (1992) argue that, because U_{eq}^i may be negative, this term is of indeterminate sign. In fact, this apparent ambiguity arises from the fact that they assumed the existence of equilibrium; it disappears once the conditions for existence in our Proposition 1 are imposed.

To see this, take the expectation of Equation (3.15) and apply definitions Equations (3.7) and (3.8) to find:

$$E_\theta \phi_e^i = \alpha_i + \beta_i + (n-1)\beta_i \tag{3.17}$$

In a symmetric equilibrium, where $\alpha_i = \alpha$ and $\beta_i = \beta$, this reduces to $E_\theta \phi_e^i = \alpha + n\beta$. However, Proposition 1 asserts that $\alpha + n\beta < 0$ is a sufficient condition for the existence of the equilibrium. Clearly, if $\phi_e^i < 0$ for all realizations of θ, then $E_\theta \phi_e^i = \alpha + n\beta < 0$. However $\phi_e^i < 0$ is exactly the restriction imposed by Equation (3.10) to guarantee existence of the equilibrium. In other words, the sufficient condition for existence eliminates the ambiguity about the sign of second term of Equation (3.16). Now consider $\phi_{\theta\theta}^i$. Simple calculations reveal

$$\phi_{\theta\theta}^i = d^2[U_{eqq}^i - \theta d' U_{qqq}^i + 2\frac{d'}{d}U_{qq}^i] \tag{3.18}$$

This should be compared to condition (3.13), for the planner. As in that case, the "uncertainty substitution effect," is negative because of risk aversion. The "uncertainty income effect" depends upon the sign of $U_{eqq}^i - \theta d' U_{qqq}^i$. Prudence with respect to environmental quality $U_{qqq}^i \geq 0$ also tends to make this negative. Notice, however, that this effect is larger for the planner, and increases with the number of countries. Cross-prudence $U_{eqq}^i \geq 0$ offsets the affects of risk aversion and prudence, and can in principal make $\phi_{\theta\theta}^i > 0$. This leads to

Proposition 4 *An increase in uncertainty about the environmental damages of emissions will increase (reduce) the emissions in the Nash equilibrium as* $U_{eqq} - n\theta d' U_{qqq} + 2n\frac{d'}{d}U_{qq}$ *is positive (negative).*

It is again informative to express this for a small risk. If we denote the Nash equilibrium in the absence of uncertainty by $\bar{e}^N$, then we can say that locally

$$e^N = \bar{e}^N - \frac{\phi_{\theta\theta}}{\phi_e}\frac{\sigma^2}{2} \tag{3.19}$$

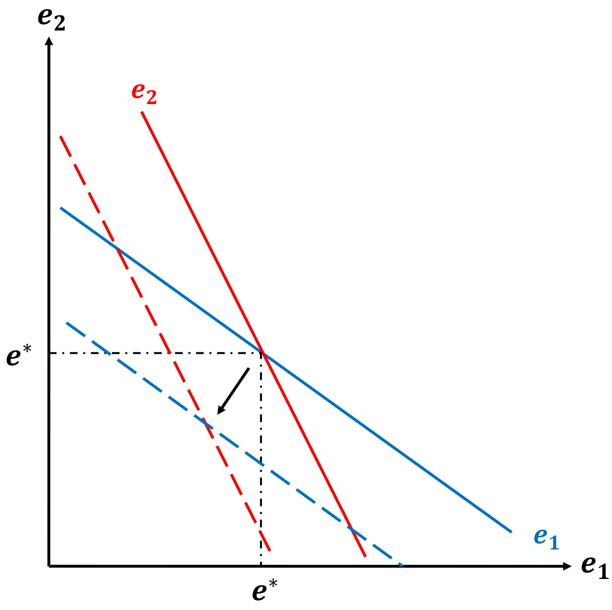
As before, both $\phi_{\theta\theta}$ and ϕ_e are evaluated at the mean of θ. Since $\phi_e < 0$ uncertainty will reduce emissions as long as $\phi_{\theta\theta} < 0$. Assuming that countries are risk averse and prudent, this will occur as in the case of the planner - unless they are also very cross-prudent.

Equation (3.19) also tells us something else. Look at the definition of ϕ_e in Equation (3.16), and recall that if $-[\theta d' U^i_{eq} + \theta d'' U^i_q - (\theta d')^2 U^i_{qq}] > 0$ – in other words if $\beta_i > 0$ – then emissions are strategic complements. Now denote equilibrium emissions when emissions are strategic substitutes by e^N_{sub} and the corresponding equilibrium when emissions are strategic complements by e^N_{comp}. Strategic complementarity makes the denominator of the last term in Equation (3.19) less negative, so that $-\frac{\phi_{\theta\theta}}{\phi_e}$ will increase. We therefore have

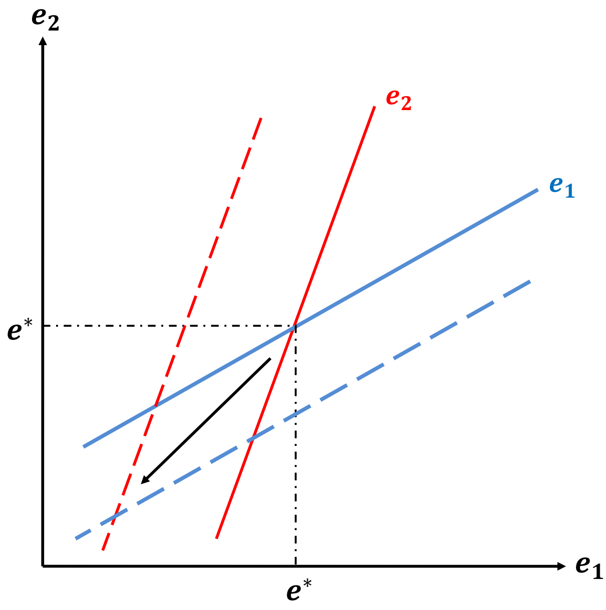
Proposition 5 *Strategic complementarity magnifies the effects of risk on emissions, and strategic substitutability dampens them. That is,* $|\frac{\partial e^N_{comp}}{\partial \sigma}| > |\frac{\partial e^N_{sub}}{\partial \sigma}|$.

This is has a straightforward geometric interpretation, as shown in Figure 3.2. However, it could have important policy implications: Strategic complementarity has the potential to greatly magnify the effects of climate risk, for good or for ill. This takes us to the question of risk and welfare.

Figure 3.2 illustrates the example when riskier damages induce each country to reduce its emissions. There are two possibilities (a) Emissions are strategic substitutes and (b) Emissions are strategic complements.



(a) Strategic Substitutes, $\frac{de_2}{de_1} < 0$



(b) Strategic Complements, $\frac{de_2}{de_1} > 0$

Figure 3.2: Uncertainty, Reaction Functions, & Equilibrium.

3.5 Welfare and Uncertainty

Bramoullé and Treich (2009) point out that environmental risk affects welfare both directly (by affecting the size of the damages) and indirectly (by changing emissions). Intuitively, the direct effect should reduce welfare. Is it possible for uncertainty to cause so much of a decline in emissions in a strategic setting that people will be better off? To address this question, consider the welfare function defined in Equation (3.2), but evaluated at the Nash equilibrium. Use the same small risk introduced in the previous section, $\theta = \bar{\theta} + \sigma\varepsilon$, with $E(\varepsilon) = 0$ and $Var(\varepsilon) = 1$. Welfare is then

$$W(e^N) = nE_\theta U[e^N, \bar{q} - (\bar{\theta} + \sigma\varepsilon)d(ne^N)] \tag{3.20}$$

Take a second-order Taylor series around the risk-less Nash equilibrium $e^N = \bar{e}^N$ and around $\varepsilon = 0$ to find

$$W(e^N) - W(\bar{e}^N) = n[U_e - \bar{\theta}d'U_q - (n-1)U_q](e^N - \bar{e}^N) + n^2 U_{qq}\frac{\sigma^2}{2} \tag{3.21}$$

We can apply the Envelope Theorem, however, to see that $U_e - \bar{\theta}dU_q = 0$. We can also employ Equation (3.19) to rewrite Equation (3.21) as

$$W(e^N) - W(\bar{e}^N) = (n-1)U_q \frac{\phi_{\theta\theta}}{\phi_e}\frac{\sigma^2}{2} + n^2 U_{qq}\frac{\sigma^2}{2} \tag{3.22}$$

The second term on the right-hand side of Equation (3.22) is the direct effect of risk. It is unambiguously negative because of risk aversion. Notice that its magnitude increases with the square of the number of countries.

The first term is the strategic effect of risk. Notice that it is magnitude (in absolute value) increases linearly with the number of countries. Recall that $\phi_e < 0$. Then there are two cases to consider, depending upon the sign of $\phi_{\theta\theta}$.

First suppose that $\phi_{\theta\theta} < 0$. Proposition 3 showed that an increase in risk will then reduce emissions, and so tend to increase welfare. In this case the direct and indirect effects of push in opposite directions. It is possible that welfare will actually increase. This is the possibility considered by Bramoullé and Treich (2009).

If, however, $\phi_{\theta\theta} > 0$ then Proposition 3 asserts that the increase in risk will raise emissions, and so reduce welfare. The direct and indirect effects of risk reinforce each other in reducing welfare.

In either case, Proposition 4 combined with Equation (3.22) tell us that the magnitude of the effect on welfare (in absolute value) will be larger in the presence of strategic complementarity than in the presence of strategic substitutability.

We may summarize all this with

Proposition 6 *If $\phi_{\theta\theta} > 0$, uncertainty about the environmental damages of emissions will reduce welfare. If $\phi_{\theta\theta} < 0$, then it is possible that it will increase welfare. Furthermore, the absolute value of the change in welfare will be greater with strategic complementarity than with strategic substitutability.*

3.6 Conclusion

We have established that an increase in uncertainty about the environmental damages of emitting will cause emissions in the Nash equilibrium to decline if the function $\phi_{\theta\theta}$ is negative. This is likely to occur if people are (1) risk averse, (2) prudent, and (3) are either cross-imprudent or not terribly cross-prudent. On introspective grounds, this seems plausible. This makes it possible *a priori* that risk may actually improve welfare. However, the magnitude of the reduction in emissions will be smaller in the presence of strategic substitutability. It is intuitively plausible (Echazu, Nocetti, & Smith, 2012) that emissions and environmental quality should be Edgeworth complements, which requires strategic complementarity. These would tend to reduce the benefits of reduced emissions. It must also be remembered that the strategic benefit of risk increases linearly with the number of countries, while the direct effect of risk-aversion increases with the *square* of the number of countries. Our priors are therefore that it is unlikely that the net effect of environmental risk should be to increase welfare.

CHAPTER 4

County-Level Determinants of Prescription Drug Consumption in Selected US States

4.1 Introduction

The 2010 US spending on hospital care, physician and clinical services, and prescription drugs accounted for about 61% of total healthcare expenditures estimated at (Martin *et al.*, 2012). The national healthcare expenditure, for the same period, was estimated at $2.6 trillion (or 17.9% of the Gross Domestic Product). The most conservative projection anticipates aggregate healthcare expenditures to reach 20.3% of GDP by 2018 (Sisko *et al.*, 2009). Although prescribed drugs expenditure in 2010 represented 10% of the total health care spending (see, Appendix I), it remains one of the fastest growing components, increasing at double digits rates up to the early 2000s (see, Appendix J). Moreover, a further rise in drug consumption is expected, as prescribed drugs are an effective and "cheaper" treatment technology.[1] This is in addition to the expansionary effects on prescription drugs consumption arising from greater insurance coverage and benefits[2] due to the 2006 Medicare Part D drug benefits and the 2010 Affordable Care Act.

Therefore, to contain the impending US healthcare expenditure upsurge a better understanding of the core drivers of prescription drugs consumption is necessary and timely. Specifically, this present research, the first to use (the most recent) county level data, also tests the flexible Box-Cox transformations model against its *a priori* restrictive nested forms (traditionally used in this line of work) for separately investigating the drivers of prescription drugs consumption in low, average, and high consumption US states. Following Panopoulou and Pantelidis (2012), six selected US states were grouped into three convergence clubs of their prescription drug ex-

1. Lichtenberg,1996, shows that an increase of 100 prescriptions results in 16.3 times hospital days, and that $1 increase in pharmaceutical expenditure results in $3.65 reduction in hospital care expenditure

2. For example, our priors have found that Medicare Part-D plans have succeeded in lowering by approximately 20% out-of-prices for enrollees (Duggan & Scott-Morton, 2010) and have increased utilization of pharmaceutical treatment (Lichtenberg & Sun, 2007).

penditures: High (Tennessee), Average (Arkansas and N. Dakota) and Low (Idaho, S. Dakota and Washington). Given the heterogeneity in pharmaceutical healthcare expenditures across the clubs, modeling the aggregate county-level data of the states would yield biased and inefficient econometric model parameter estimates and engender faulty policy inferences.

The remainder of this research proceeds as follows. Section 2 reviews relevant literature on the determinants of prescription drugs consumption. Section 3 presents the data and research methodology. Section 4 presents and discusses the empirical results. Finally, section 5 concludes with the policy inferences of the study findings.

4.2 Previous Literature

Health factors: The percentage of individuals with a BMI greater than 30, the percentage of adults reporting smoking, and the percentage of adults reporting a fair or poor health are three health behavior and health status factors. A number of diseases (e.g., sleep apnea, cardiovascular, hypertension, diabetes, and all type of cancer linked to obesity translates into greater prescription drugs consumption (Vandergrift & Datta, 2006). Kit *et al.* (2012) find that, between 2005 and 2008, 56.4% of the US adults consume one or more prescribed medication, and a quarter of those prescriptions were for hypertension related illnesses (e.g., clinical depression and diabetes). Consequently, each of these three health factors is *a priori* expected to raise prescribed drugs consumption.

Access factors: County-level total prescription drugs consumption is likely to increase both with greater number of pharmacies and other health care providers. Okunade and Suraratdecha (2006), looking at selected OECD countries (Austria, Belgium, Italy, and UK), conclude that pharmaceutical spending increases with the number of physicians.[3] This could be justified by the "hypothesis of provider-induced demand for healthcare services" which states that because of reimbursement schemes (See, Weiner *et al.*, 1991, Lavizzo-Mourey and Eisenberg, 1990)

3. Suraratdecha (1996), however, using 1980-1990 pooled data of the US states, report an insignificant linkage of per capita physician expenditure to per capital prescription spending

and for job security reasons, medical care personnel may have incentives to prescribe "unnecessary"F treatments for patients. Medical care personnel being potential enablers (see Granlund & Rudholm, 2012; Karatzas, 1992) the primary care provider and the mental health provider rates are likely to raise prescription drugs consumption. Similarly, greater access to community pharmacies at the county level could also increase Prescription drugs consumption.

Socio-economic factors: There is evidence in the healthcare literature indicating that a rise in the median household income leads to greater prescription drugs spending (Murillo & Saez, 1994; Newhouse, 1977). Alexander *et al.*, (1994) report the US income elasticity for ethical drugs to be close to 1.79. Income can have both a direct and an indirect effect on prescription drugs consumption. The direct effect states that wealthier individuals tend to have greater concerns for their health (Benezeval & Judge, 2001; Grossman& Kaestner, 1997). Thus, they are expected to encounter the healthcare system more frequently. The indirect effect expects individuals with higher incomes to have better insurance coverage benefits to purchase more pharmaceutical goods (Leibowitz *et al.*, 1985). Brow (2004), in his study of the impact that the US income inequality has on consumption, concludes that a rising income inequality leads to falling consumption. Consequently, we here test for the first time in the specific context of ethical drugs consumption the role of income inequality, captured using GINI coefficients.
Individuals with more education tend to have a better health status and they consume more prescription drugs. They are able to efficiently transform health information into improved health status. They also place more emphasis on preventive care and have greater access to health services. Also, greater formal schooling comes with higher earnings. We can thus, hypothesize prescription drugs consumption to also increase with education level (Lichtenberg and Lleras-Muney, 2005). More specifically, Cutler and Lleras-Muney (2010) find that income, insurance and family background account for about 30% of the education gradient.

Demographic factors: Population aging is associated with greater susceptibility to illnesses and the need for contacts with the healthcare system, including prescription drugs. Moreover, women generally tend to use the healthcare system more frequently than men. This tendency emanates from two possible sources. First, women have higher life expectancies[4] and therefore have longer contacts and duration with the healthcare system. Second, women often use health services for gender-related issues such as fertility and fecundity related concerns (Hunt-Mccool *et al.*, 1997). With the longer and more frequent encounters with the healthcare system, an increase in the female population could increase prescription drugs consumption (Cylus *et. al.*, 2010). Gu *et al.*, (2010), reporting on the prescription drugs used in the US, claim that the percentage of individuals in the US population using at least one prescription medication between 2007 and 2008 was about 10 points higher for women (53.3 *versus* 43.2 for men).

Many studies in the healthcare literature find racial disparities in both access and usage of health services (See, Reed *et al.*, 2003; Schneider *et al.*, 2002). Schore *et al.*, (2003) study of Black and White Medicaid pharmacy use concludes that in 8 out of the 10 states studied, Black beneficiaries have significantly fewer prescriptions filled. Similar results were found for the Medicare beneficiaries where Black and Hispanic population groups use 10 to 40% fewer medications than their White counterpart. In this current study, an increase in the minority population proportion is expected to reduce prescription drugs consumption.

4.3 Data and Methodology

Data

The six states (Arkansas, Idaho, N. Dakota, S. Dakota, Tennessee and Washington) considered in this study are partitioned into three regions (Low, Average, and High) based on convergence[5] of their prescription drug expenditures. Panopoulou and Pantelidis (2012) study convergence in the different components of the aggregate healthcare expenditure for the US states, and conclude the existence of four separate convergence clubs (See, Appendix K) for prescription drugs spending. For this study, the low spending states belonging to a convergence club comprise Idaho (44 counties), S. Dakota (66 counties), and Washington (39 counties). The average spending states, belonging to a separate convergence club, comprise Arkansas (75 counties) and

4. Xu *et al.*, (2010) find that the US girls born in 2008 are expected to live 80.3 years, compare to 75.2 for boys

5. The notion of convergence in healthcare expenditures is similar to that of income convergence in neoclassical growth models (Solow, 1956).

N. Dakota (53 counties). Finally, a separate convergence club comprises the high spending state of Tennessee (95 counties).[6]

Data for study are from two main sources. First is the 2011 *SK&A*[7] *National Pharmacy Market Report* on counts of prescriptions filled and the number of pharmacies in each county. The data cover surveys of 4,251 community pharmacies across the low, average, and high prescription drugs consumption clubs. Second, data on the controlling health factors were obtained from *The University of Wisconsin Population and Health Institute's County Level Rankings*. These factors are grouped into four internally consistent categories: demographics, health, socio-economic, and access. Table 4.1 is a summary presentation of the main variables used in this study.

Table 4.1: Prescription drugs Data Variables and Sources

	Variables	**Source**
	Prescription volume (Rx)	SK&A National Pharmacy Market Report
Health	Percent of adults reporting fair or poor health	Behavioral Risk Factor Surveillance System
	Percent of adults smoking $\geq$ 100 cigarettes	
	Percent of adults that report a $BMI \geq 30$	Centers for Disease Control and Prevention
Access	Primary Care Provider rate per 100K (PCP)	Health Resources & Services Administration
	Mental Health Provider rate (MHP)	
	Number of Pharmacies (Pharmacies)	SK&A
	% of population $\leq$age 65 without insurance	Small Area Health Insurance Estimates
Socio-Econ	% of adults with post-secondary education (PSED)	American Community Survey
	% of 16+ years old unemployed (Unemployed)	Bureau of Labor Statistics
	Median household income (Income)	Small Area Income and Poverty Estimates
	% of children $\leq$ age 18 in poverty	
Demographic	% 65 and older (P65)	US Census Bureau
	% African American (Black)	
	% Hispanic	
	% female	
	% rural	

6. Our dataset comprises a total of 372 counties

7. SK&A is part of Cegedim family, a global Technology and Services Company specialized in healthcare.

Summary statistics in Table 4.2 indicate that when compared to the other regions, those in high convergence club counties tend to consume more prescriptions, are less healthy, have less access to physicians, are less educated and have higher poverty rates.

Table 4.2: Prescription Drugs Data Summary Statistics

	Variable	**High Spenders**	**Average Spenders**	**Low Spenders**	**Total**
	Prescription per capita	1.603	1.566	1.521	1.558
Health	Smokers	25.031	21.504	18.503	20.858
	Obese	32.768	32.273	30.154	31.551
	Fair-Poor health	21.838	16.975	14.301	16.971
Access	PCP	76.074	97.421	103.484	93.701
	Pharmacies	16.659	8.051	13.626	12.503
	Uninsured	21.863	22.281	22.517	22.269
Socio-Econ	PSED	42.379	54.766	57.306	52.62
	Income	37,784.04	39,349.57	43,006.06	40,414.33
	Children in Poverty	29.526	25.852	22.758	25.551
	Unemployed	11.301	6.81	7.742	8.33
Demographics	Population	27,627.30	60,552.88	50,685.29	66,276.36
	P65	15.427	18.028	16.142	16.609
	Black	7.585	9.696	0.714	5.559
	Hispanic	2.88	3.363	7.441	4.873
	Female	50.625	50.306	49.77	50.173
	Rural	68.808	72.965	66.118	69.161

Methodology

Healthcare data including prescription drugs consumption and health expenditures tend to be skewed. As a result, the commonly used ordinary least squares (OLS) estimation method will be inefficient. Therefore, it is important, in order to make correct policy inferences, to opt for an estimation technique which can accommodate the skewed data distribution of the response variable. For investigating the relationship between prescription drug counts and its explanatory variables, we propose using the more flexible Box-Cox (Box & Cox, 1964) power family of transformations model for normalizing the response distribution and for selecting the appropriate functional form for modeling each convergence club data. The Box-Cox model is as follows:

$$Y^{(\lambda)} = \begin{cases} \frac{Y^{\lambda}-1}{\lambda} = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 Z & \text{if } \lambda \neq 0 \\ Log(Y) = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta 4Z & \text{if } \lambda = 0 \end{cases} \tag{4.1}$$

where Y_i is the Prescription drugs volume in county i; X_{ji}, respectively, are the health, access, and economic factors ($j = 1,..,4$); Z is set of control variables; ε_i the independent and normally distributed random variables with constant variance and zero mean, and λ is estimated optimal parameter of the Box-Cox transformation based on maximum likelihood criterion.

To test whether the variables across the three clubs are statistically different, we conduct a multivariate analysis of variance. The corresponding *p-levels* of the *MANOVA F statistics* show that prescription drugs and most of the control variables are significantly different for the three convergence club regions (see, Table 4.3).

Table 4.3: Multivariate Analysis of Variances Between Clubs

	Variables	**F-Statistic**	**Pr > F**	**N**
	Prescription	2.65	0.0724	340
Health factors	Smokers	29.45	<.0001	324
	Obese	18.92	<.0001	372
	Fair-Poor health	59.64	<.0001	346
Access	PCP	4.82	0.0087	334
	Pharmacies	2.59	0.0768	340
	Uninsured	3.08	0.0471	372
Socio-Economic	PSED	48.59	<.0001	372
	Income	14.35	<.0001	372
	Children in poverty	16.77	<.0001	372
Demographic	P65	9.54	<.0001	372
	Black	27.48	<.0001	372
	Hispanic	16.83	<.0001	372
	Female	8.78	0.0002	372
	Rural	1.89	0.153	372

4.4 Empirical Results

As earlier stated the Box-Cox power family of transformations technique is used to stabilize the variances and it transform data to normality by pulling in the tails of the distribution. The λ power transformation parameter estimate for our dependent variable (count prescription drugs) was first determined for the entire data and then separately for each convergence club data set. Table 4.4 contains the log-likelihood (*LL*) ratio statistic (*LR Stat*) results for testing the statistical significance of lambda λ equal to -1 (inverse), 0 (log), and 1 (linear) functional forms against the estimated λ^*, considered optimal using the unrestricted Box-Cox transformation regressions. The Box-Cox procedure outputs optimal λ estimates (at the lowest log-likelihood score statistic) to be 0.217 for the pooled data model, 0.567 for the high convergence club model, 0.696 for the average expenditure convergence club data, and 0.087 for the lowest expenditure convergence club areas. Other than for the lowest convergence club[8] states model the optimal model λ estimates reject fitting of the traditionally restricted log or linear functional forms (see, Appendix L). Graphical displays of the Box-Cox transformation models yielding optimal λ values are in Appendix M - P.

Table 4.4: Testing The Box-Cox Transformation Model Against Nested Forms

Clubs	λ	**LL**	**LR Stat**
Pooled Model	-1	-3594.88	973.56
	0	-3124.53	32.86
	1	-3312.85	409.49
	0.217	**-3108.1**	**434.12**
High Spenders	-1	-729.301	143.47
	0	-679.868	44.6
	1	-702.488	89.84
	0.568	**-657.57**	**183.77**
Average Spenders	-1	-1199.69	372.06
	0	-1040.57	53.79
	1	-1052.61	77.88
	0.696	**-1013.67**	**207.61**
Low Spenders	-1	-1519.46	346.23
	0	-1347.56	2.43
	1	-1460.38	228.06
	0.087	**-1346.34**	**163.6**

Applying Equation 1, the estimated λs of the Box-Cox procedure are then used to transform our dependent variable. Table 4.5 summarizes the findings. The highly significant dummy variables controlling for the low and average convergence club memberships, in the first column of Table 4.5, indicate the need to estimate separate models for the three clubs. For Tennessee counties (high spenders), we included dummies for testing the existence of any differences in east

8. For $\lambda = 0$ the log-likelihood ratio test statistic suggests a log transformation of the response variable for the low expenditure convergence club observations.

(wealthier) and middle Tennessee relative to west Tennessee counties (poorest areas), and found no significant differences in prescription drugs consumption. In the low prescription expenditure convergence region, the model estimation results confirm prescription drugs consumption as significant less in the states of Idaho and S. Dakota relative to Washington. Also, for the average spending region, drugs consumption in Arkansas counties is significantly higher than in N. Dakota. In general, the adjusted R^2 values indicate that the right hand side variables in the estimated models capture a most of the variations in ethical drugs consumption at the county level. Since the dependent variable is power transformed, interpretation of the coefficient estimates is not straightforward. Therefore Appendix Q contains the computed marginal effects for the significant variables in high and average spending club regions.

Table 4.5: Box-Cox Regression Model Estimates By Convergence Clubs

		Pooled Model	**High Spenders**	**Average Spenders**	**Low Spenders**
	$\hat{\lambda}$	0.21689	0.56794	0.69565	0.08681
	Intercept	-13.55	-108.8	186.7	10.17**
		(-0.55)	(-0.08)	(0.04)	(2.41)
Health Factors	Obese	-0.0402	-9.737	16.19	0.0102
		(-0.28)	(-1.06)	(0.74)	(0.39)
	Smokers	0.225**	-2.772	10.24	0.0657***
		(2.57)	(-0.57)	(0.57)	(3.19)
	Fair-Poor	0.0151	1.553	-48.63***	-0.113**
		(0.11)	(0.21)	(-3.35)	(-2.13)
Access to Care	PCP	0.0203***	1.592***	0.476	0.00442***
		(2.84)	(3.64)	(0.83)	(3.37)
	Uninsured	0.288	20.61	-35.16	0.0127
		(1.59)	(1.57)	(-1.27)	(0.39)
	Pharmacies	0.247***	27.91***	177.9***	0.00877*
		(4.70)	(27.45)	(21.24)	(1.96)
Socio-Economics	PSED	0.00476	4.099	22.94**	-0.00517
		(0.07)	(1.15)	(2.20)	(-0.42)
	Income	0.000682*	0.0359**	-0.0940	0.0000112
		(1.77)	(2.50)	(-0.95)	(0.12)
	Income^2	-5.56E-09	-3.31. E-7***	8.77E-7	-8.61E-11
		(-1.55)	(-3.13)	(0.83)	(-0.10)
	GINI	-0.0237	-6.556	49.35	-0.0516
		(-0.13)	(-0.48)	(1.35)	(-1.51)
Demographics	Black	-0.117***	-4.156	-24.04***	0.156
		(-2.70)	(-1.51)	(-3.18)	(1.40)
	Hispanic	-0.0949	-17.31	-23.23*	0.00819
		(-1.06)	(-1.22)	(-1.78)	(0.43)
	P65	-0.516***	-1.970	-89.46**	-0.0336
		(-4.03)	(-0.15)	(-2.51)	(-1.49)
	Female	0.852**	4.700	45.16	0.0746
		(2.44)	(0.36)	(0.44)	(1.40)
	Rural	-0.220***	-5.904***	-9.832**	-0.0243***
		(-8.22)	(-3.27)	(-2.08)	(-5.45)
Controls	High Spenders	7.449***			
		(4.51)			
	Medium Spenders	2.717**			
		(2.44)			
	East TN		45.67		
			(0.73)		
	Middle TN		52.53		
			(0.97)		
	AR			1034.3**	
				(2.06)	
	ID				-0.440*
					(-1.68)
	SD				-0.861***
					(-2.96)
	Number of Counties	**271**	**59**	**94**	**118**
	Adj. R^2	**0.817**	**0.988**	**0.960**	**0.741**

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *T-statistics in parentheses*

Recall that Box-Cox $\beta = (X'X)^{-1}(X'Y)^{(\lambda)}$ *where* $Y^{(\lambda)} = (Y^{\lambda} - 1)\lambda$

Effects of health behavioral factors

Surprisingly for the high spenders club, population health status does not have a statistically significant impact on prescription drugs consumption. This could be explained by the club's inherently poor population health status and low socio-economic conditions (e.g., lack of health knowledge) as barriers for accessing adequate medical care services. For example, a percentage point rise in adults reporting fair or poor health reduces prescription drugs consumption 11.3%, and a one percent rise in the number of smokers raises prescribed drugs consumption 6.57%.

Access factors

The access to care variables appear to be the most significant factors driving prescription drugs consumption across the three convergence spending clubs. If primary care providers increase by 1 per 100,000 of the population it would significantly raise the prescription drugs consumption in Tennessee by 252 count units and by 0.44% for the low spenders club. Controlling for other factors, these findings could suggest that doctors in these counties are more generous prescribers. Moreover, the presence of an additional pharmacy in a county significantly increases total annual consumption of prescribed drugs by 4422 in the high spending club area, by 4739 in the average spending states, and by 0.87% in the low spending club region. The significantly higher estimate in the average spending area reflects the fewer pharmacies per 100,000 of the population in its counties (i.e., 13.295 per 100,000 *versus* 23.883 per 100,000 in the low and 60.299 per 100,000 in the high spending states).

Socio-economic factors

Intuitively, we anticipate the more highly educated to transform health information into better health status, to have better access to health services, and have greater concern for their health. Our estimation results are only significant for the average spending club region. A percentage point increase of adults with post secondary education in this region raises annual prescription drugs consumption by 611 counts.

Prescription drugs consumption significantly increases with income at a decreasing rate in the low spending club areas. Further, the income elasticities for prescription drugs consumption is positive and less than one (for computation, see, Appendix R), suggesting that prescription drugs are a necessity, as anticipated. The estimated income elasticity for the aggregated model (0.461) indicates that prescription drug is a necessity in general. However, we found an income elasticity of 0.535 for the high spending Tennessee. These different findings across the convergence club areas attest to the need to consider modeling homogeneous regions, as in the present study.

Moreover, while not statistically significant but correctly signed, our model results suggest that rising income inequalities reduces prescription drugs consumption in the three convergence club spending groups. This effect points to the tendency for greater public sector prescription drug subsidies in areas of large income disparities, which would naturally lead to further increases in healthcare spending.

Demographics

If the percentage of Blacks in a county increases by one percent, prescription drugs consumption diminishes 640 in the average spending states. Similarly, a percent point increase in Hispanics reduces consumption by 620 units. Moreover, a higher rural population percentage is associated with lower prescription drugs use. Specifically, a percent increase in rural population reduces prescription drugs usage by 935, 267, and by 2.43%, respectively in high, average and low spending club areas. One possibility is the tendency for the rural population to engage in the use of more alternative or traditional medicines. To further investigate the most potent drivers of prescription drugs consumption, across the convergence clubs, we compute the beta coefficient (see, Appendix R). The standardized beta coefficients signal that the number of pharmacies (that is, an access variable), the median household income (that is, an economic factor), and the percent of rural population (a demographic factor) in a given county are the most potent factors determining prescription drugs consumption.

4.5 Conclusion

The primary goal of this research was to determine the core drivers of US prescription drugs consumption. The analyses were conducted for three different groups (high, average, and low) of prescription drugs consumers. Based on their convergence in prescription drug expenditures, six selected states were partitioned as follows: Tennessee in the high, Arkansas and N. Dakota in the average, and Idaho, S. Dakota and Washington in the low spending region.

Given the tendency for healthcare data to be skewed, we anticipated that fitting the commonly used linear and log-linear functional forms to our data can lead to erroneous regression model parameter estimates and misleading policy inferences. To determine the best model for each region, we applied the more flexible Box-Cox transformations model, using 2011 county data. Our aggregate data model findings significantly differ from those of the individual convergence club regions. The Box-Cox transformation estimates of the optimal lambdas also differ across regions. This attests to the need to consider separately modeling data of internally homogeneous regions in healthcare consumption, expenditure, or cost studies.

Several additional conclusions derive from our regression model estimate. First, more in depth consideration should be given to access to care measures as they have the most significant impact on the degree to which individuals consume ethical drugs. The wider the access to community pharmacies in a county the more likely is the population to use prescription drugs. Second, the results suggest that primary care providers in the high and low spending states tend to prescribe more. Therefore, in order to reduce provider induced demand, stricter controls could be implemented in high and low consumption club areas. Third, income increases prescription drugs consumption at a decreasing rate in high and low spending regions. The median household income is only significant in Tennessee and the income elasticities indicate that prescription drugs are a necessity. This calls for implementing specific health policy reforms in the high spending region. Moreover, in order to contain high US healthcare spending, it is important to reduce income inequalities. Fourth, minority and rural population groups, on average, consume less prescription drugs than their White and urban counterparts.

This study is the first insightful analysis of the determinants of prescribed drugs consumption based on 2011 county level data of low, average, and high expenditure convergence club states in the US. One potentially fruitful avenue for future work is expanding the county-level data coverage and model estimations for specific income quintiles, age profiles, and ethnic groups to include all of the counties in the six US pharmaceutical spending convergence club states. An interesting question would be to investigate the impact the length of physician's practice and prescriber gender on prescription drug consumption.

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APPENDIX A Health Outcomes Variables and Sources

		MEASURES	SOURCES
OUTCOMES	**Mortality**	Premature death rateYears of potential life lost before age 75 (YPLL-75)	Vital Statistics, National Center for Health Statistics (NCHS)
	Morbidity	Mean physically unhealthy days/month for adults	Behavioral Risk Factor Surveillance System (BRFSS)
		Mean mentally unhealthy days/month for adults	
		Percent of live births with low birth weight ($< 2500g$)	Vital Statistics, NCHS
FACTORS	**Health behavior**	Percent of adults that report smoking at least 100 cigarettes and that they currently smoke	BRFSS
		Percent of adults that report a $BMI \geq 30$	CDC, National Center for Chronic Disease Prevention and Health Promotion
		Teen birth rate/ 1,000 female $15-19$	Vital Statistics, NCHS
	Access to Care	Percent of population $< age65$ without health insurance	CCPS, Small Area Health Insurance Estimates (SAHIE)
		Primary care provider rate per 100K (PCP)	Health Resources and Services Administration, Area Resource File (ARF)
		Mental health providers (MHP)	Health Resources & Services Administration (HRSA)
	Quality of Care	Hospitalization rate for ambulatory-care sensitive conditions per 1,000 Medicare enrollees (ACSC)	Medicare claims/Dartmouth Atlas
		Percent of diabetic Medicare enrollees that receive HbA1c screening (HbA1c)	
	Education	Averaged freshman graduation ratePercent of ninth grade cohort that graduates in 4 years (AFGR)	National Center for Education Statistics
		Percent of population age 25+ with 4 year college degree or higher	Decennial Census, American Community Survey
	Employment	Percent of population age 16+ unemployed but seeking work	Local Area Unemployment Statistics, Bureau of Labor Statistics
	Poverty	Percent of children in poverty	Census/CPSSmall Area Income and Poverty Estimates (SAIPE)
		Gini coefficient of income inequality	Decennial Census
	Family and Social Support	Percent of adults without social/emotional support	BRFSS
		Percent of all households that are single-parent households	Decennial Census, ACS
	Environmental Quality	Annual number of unhealthy air quality days due to ozone	CDC-Environmental Protection Agency (EPA) Collaboration
		Annual number of unhealthy air quality days due to fine particulate matter	

Notes Appendix B-E

The estimation outputs labels are as follows:

(i) The joint regression

(ii) The joint regression with region dummy

(iii) The disaggregated regressions, by region

(iv) The disaggregated regressions, by region, with a set of control variables

(v) The disaggregated regressions, by region, with a set of control variables, and state fixed effect

APPENDIX B: Premature Death Rate Estimations Output

Variables	(i)	(ii)	(iii)		(iv)		(v)	
			NE	S	NE	S	NE	S
Intercept	8.598***	8.692***	8.469***	9.059***	187.6***	98.60***	179.8***	108.2***
	(-141.63)	(-154.66)	(-48.28)	(-141.93)	(-10.28)	(-7.23)	(-12.82)	(-6.34)
Obese	0.0315***	0.0236***	0.0288***	0.0200***	0.0213***	0.0198***	0.0172***	0.0192***
	(-33.91)	(-26)	(-15.96)	(-18.9)	(-13.4)	(-15.99)	(-9.32)	(-6.44)
Uninsured	0.00398***	-0.00434***	0.00213	-0.00580***	-0.00804***	-0.00449***	-0.00765**	-0.00549**
	(-6.5)	(-6.19)	(-1.32)	(-7.63)	(-6.25)	(-5.27)	(-4.43)	(-4.49)
PCP	0.0000566	-0.000026	0.000252*	0.000147	0.0000506	0.0000845	-0.00000968	0.000132
	(-0.91)	(-0.41)	(-2.06)	(-1.88)	(-0.41)	(-1.04)	(-0.05)	(-0.88)
MHP	-0.000260***	-0.000131***	-0.0000969***	-0.00145***	-0.0000964***	-0.00106***	-0.0000753***	-0.000846**
	(-5.05)	(-6.15)	(-7.35)	(-5.94)	(-9.40)	(-4.89)	(-12.08)	(-4.39)
ACSC	0.00129***	0.00129***	0.00263***	0.00112***	0.00204***	0.00112***	0.00226**	0.00103***
	(-12.05)	(-13.26)	(-7.56)	(-11.4)	(-7.04)	(-11.05)	(-4.76)	(-4.67)
HBA1C	-0.00498***	-0.00443***	-0.00529***	-0.00406***	-0.00331**	-0.00328***	-0.00330*	-0.00230**
	(-10.43)	(-10.13)	(-3.38)	(-9.04)	(-2.59)	(-7.12)	(-2.38)	(-3.52)
AFGR	-0.00410***	-0.00290***	-0.00432***	-0.00287***	-0.00190**	-0.00177***	-0.00392**	-0.00162
	(-13.79)	(-9.87)	(-4.95)	(-9.32)	(-2.98)	(-5.09)	(-3.95)	(-2.11)
Unemployed	0.0104***	0.00503***	0.00794	0.00340**	0.0131***	0.00177	0.0202*	0.00543
	(-7.72)	(-4.02)	(-1.92)	(-2.65)	(-3.85)	(-1.38)	(-3.1)	(-1.96)
Singleparent	-0.000920**	0.000625*	0.000478	0.00114***	0.00421***	0.00288***	0.00332**	0.00259***
	(-3.17)	(-2.24)	(-0.62)	(-3.82)	(-5.61)	(-7.01)	(-4.57)	(-5.94)
Ozone-days	-0.00324***	-0.00318***	0.00208*	-0.00498***	0.00142	-0.00342***	0.00085	-0.00367*
	(-6.34)	(-5.80)	(-2.02)	(-7.79)	(-1.5)	(-5.10)	(-0.68)	(-2.86)
Region		0.238***						
		(-22.38)						
Over65					0.0218***	0.00762***	0.0205***	0.00744*
					(-12.23)	(-8.35)	(-6.81)	(-3.1)
Female					0.0125***	-0.0000765	0.0112*	0.000334
					(-3.54)	(-0.04)	(-2.56)	(-0.15)
Rural					0.00143***	0.000214	0.000883*	0.000469
					(-6.55)	(-1.53)	(-2.42)	(-1.46)
Hispanic					0.0000135	-0.000985***	-0.000774	-0.000337
					-0.01	(-3.46)	(-0.62)	(-1.29)
Black					0.00741***	0.000686**	0.00701**	0.000935
					(-8.44)	(-2.82)	(-3.58)	(-1.71)
Year					-0.0897***	-0.0447***	-0.0856***	-0.0495***
					(-9.89)	(-6.58)	(-12.32)	(-5.83)
N	3791	3791	706	3085	706	3085	706	3085
R^2	0.580	0.640	0.540	0.464	0.738	0.503	0.696	0.387
$Adj-R^2$	0.579	0.639	0.533	0.462	0.732	0.500	0.689	0.384

Note: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$; *T-statistics in parentheses*

APPENDIX C: Physically Unhealthy Days per Month Estimations Output

Variables	(i)	(ii)	(iii)		(iv)		(v)	
			NE	S	NE	S	NE	S
Intercept	0.982***	1.065***	1.068***	1.209***	110.7***	74.04***	99.22***	69.56*
	(19.04)	(20.21)	(11.02)	(17.79)	(4.82)	(4.05)	(4.81)	(3.03)
Obese	0.0120***	0.00787***	0.00797***	0.00778***	0.0110***	0.0167***	0.0126**	0.0168***
	(10.88)	(6.49)	(3.87)	(5.41)	(5.43)	(10.41)	(4.48)	(6.7)
Uninsured	-0.000138	-0.00455***	-0.0025	-0.00521***	-0.00452**	-0.00622***	-0.00607	-0.00585*
	(-0.18)	(-4.55)	(-1.74)	(-4.54)	(-2.65)	(-4.92)	(-2.26)	(-2.77)
PCP	-0.000612***	-0.000651***	-0.000250*	-0.000794***	-0.000317***	-0.000554***	-0.000390**	-0.000553**
	(-8.17)	(-8.59)	(-2.45)	(-8.26)	(-3.36)	(-5.72)	(-3.63)	(-3.34)
ACSC	0.00121***	0.00120***	0.00277***	0.00108***	0.00229***	0.000723***	0.00280***	0.000816*
	(6.88)	(6.93)	(5.42)	(6.01)	(4.41)	(3.98)	(9.95)	(2.71)
AFGR	-0.00108**	-0.000497	-0.00313***	-0.000216	-0.00272***	-0.00124**	-0.00309**	-0.00161*
	(-2.96)	(-1.34)	(-4.24)	(-0.52)	(-3.60)	(-2.73)	(-4.12)	(-2.74)
Unemployed	0.0132***	0.0106***	0.00429	0.0107***	0.000249	0.0113***	0.00142	0.0121*
	(-8.2)	(-6.54)	(-0.97)	(-6.23)	(-0.05)	(-6.1)	(-0.19)	(-2.89)
Singleparent	-0.00187***	-0.00104**	0.00139	-0.00138**	0.00537***	0.00145*	0.00473**	0.00121
	(-4.92)	(-2.63)	(1.54)	(-3.07)	(4.82)	(2.38)	(3.29)	(1.43)
Ozone-days	-0.00354***	-0.00352***	-0.00135	-0.00411***	0.0015	-0.00287***	0.00263	-0.00256*
	(-6.93)	(-6.69)	(-1.42)	(-6.47)	(1.4)	(-4.66)	(2.01)	(-2.77)
Region		0.112***						
		(8.96)						
Over65					0.00712**	0.00475***	0.0106*	0.00395
					(2.74)	(3.72)	(2.36)	(1.35)
Female					0.0149*	-0.0015	0.00973	-0.00145
					(2.56)	(-0.69)	(1.41)	(-0.49)
Rural					0.000291	0.000476*	-0.000279	0.00038
					(0.95)	(2.42)	(-0.35)	(0.9)
Hispanic					0.00402***	-0.000369	0.00365**	-0.00088
					(4.24)	(-0.93)	(3.88)	(-1.44)
Black					-0.00408***	-0.00402***	-0.00387*	-0.00386**
					(-5.34)	(-11.16)	(-3.20)	(-4.38)
Year					-0.0550***	-0.0363***	-0.0492***	-0.0341*
					(-4.82)	(-3.99)	(-4.82)	(-2.99)
N	3543	3543	696	2847	696	2847	696	2847
R^2	0.224	0.241	0.257	0.167	0.337	0.219	0.349	0.173
$Adj-R^2$	0.222	0.239	0.247	0.164	0.322	0.215	0.335	0.169

Note: $^{*}p<0.05$, $^{**}p<0.01$, $^{***}p<0.001$; *T-statistics in parentheses*

APPENDIX D: Mentally Unhealthy Days per Month Estimations Output

Variables	(i)	(ii)	(iii)		(iv)		(v)	
			NE	S	NE	S	NE	S
Intercept	1.252***	1.275***	1.204***	1.378***	140.9***	57.84**	134.2***	64.41**
	(20.64)	(20.59)	(10.8)	(17.34)	(5.63)	(2.69)	(5.05)	(3.35)
Obese	0.00691***	0.00567***	0.0117***	0.00353*	0.0112***	0.0146***	0.0103*	0.0138***
	(6)	(4.46)	(5.45)	(2.18)	(5.05)	(7.81)	(3.03)	(5.54)
Uninsured	-0.00390***	-0.00527***	-0.00536**	-0.00564***	-0.00899***	-0.00428**	-0.0103*	-0.00656**
	(-4.28)	(-4.44)	(-2.95)	(-4.15)	(-3.67)	(-2.63)	(-3.09)	(-3.28)
MPH	-0.000112**	-0.0000929**	-0.0000689*	-0.00074	-0.0000616*	0.0000459	-0.0000501***	0.000317
	(-2.82)	(-2.63)	(-2.42)	(-1.91)	(-2.10)	(0.13)	(-6.83)	(0.95)
PCP	-0.000593***	-0.000607***	-0.000470***	-0.000539***	-0.000459***	-0.000638***	-0.000584*	-0.000687***
	(-7.53)	(-7.71)	(-4.14)	(-4.07)	(-3.81)	(-4.71)	(-2.77)	(-6.07)
AFGR	-0.00139**	-0.00120**	-0.00276***	-0.00107*	-0.00210*	-0.00245***	-0.00377*	-0.00283**
	(-3.13)	(-2.63)	(-3.31)	(-2.15)	(-2.25)	(-4.48)	(-3.06)	(-3.59)
Unemployed	0.00833***	0.00751***	0.00284	0.00769***	0.00082	0.00909***	0.00226	0.0105**
	(4.25)	(3.76)	(0.5)	(3.63)	(0.13)	(4.17)	(0.2)	(3.35)
Singleparent	-0.000713	-0.000457	0.00146	-0.000506	0.00622***	0.00116	0.00580*	0.00151**
	(-1.63)	(-1.00)	(1.47)	(-0.96)	(5.42)	(1.6)	(3.01)	(3.91)
Ozone-days	-0.00105	-0.00104	0.00146	-0.00149*	0.00367**	-0.000901	0.00388*	0.000143
	(-1.92)	(-1.89)	(1.4)	(2.27)	(2.64)	(1.32)	(3.09)	(0.14)
Region		0.0361*						
		(2.54)						
Over65					0.0116***	0.00445**	0.0127**	0.00368
					(3.94)	(3.01)	(3.31)	(1.82)
Female					-0.00726	0.00314	-0.0125	0.000423
					(-0.93)	(1.16)	(-1.49)	(0.11)
Rural					-0.000151	-0.000671**	-0.000763	-0.000815*
					(0.40)	(-2.75)	(-1.80)	(-2.93)
Hispanic					0.000457	-0.00216***	-0.000418	-0.00238***
					-0.36	(-3.85)	(-0.50)	(-5.26)
Black					-0.00168	-0.00448***	-0.00155	-0.00575***
					(-1.59)	(-10.12)	(-0.85)	(-6.66)
Year					-0.0694***	-0.0283**	-0.0659***	-0.0314**
					(-5.58)	(-2.64)	(-4.96)	(-3.28)
N	3560	3560	696	2864	696	2864	696	2864
R^2	0.068	0.07	0.168	0.055	0.232	0.103	0.234	0.089
$Adj-R^2$	0.066	0.067	0.159 0.052	0.216	0.099	0.218	0.085	

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *T-statistics in parentheses*

APPENDIX E: Low Birth Weight Rates Estimations Output

Variables	(i)	(ii)	(iii)		(iv)		(v)	
			NE	S	NE	S	NE	S
Intercept	1.607***	1.687***	1.887***	1.734***	39.67*	9.238	59.20*	11.32
	(43.37)	(46.39)	(24.28)	(41.03)	(2.36)	(0.95)	(2.51)	(1.07)
Obese	0.0211***	0.0180***	0.00208	0.0206***	0.00857***	0.00668***	0.00639**	0.00418*
	(25.4)	(21.58)	(1.1)	(22.7)	(5.48)	(7.93)	(3.43)	(2.39)
Teenbirth	0.00206***	0.00136***	0.00435***	0.00127***	0.00216***	0.00177***	0.00200*	0.00208***
	(12.23)	(7.77)	(7.74)	(6.94)	(4.14)	(10.43)	(3.01)	(8.24)
Uninsured	-0.00154**	-0.00483***	-0.000693	-0.00476***	-0.00345*	-0.00372***	-0.00606*	-0.00453***
	(-3.02)	(-8.45)	(-0.51)	(-7.63)	(-2.39)	(-6.23)	(-2.65)	(-5.60)
PCP	0.000345***	0.000303***	-0.0000291	0.000378***	-0.000244***	0.000141*	-0.000153	0.0000566
	(5.15)	(4.86)	(-0.34)	(5.96)	(-3.82)	(2.29)	(-1.02)	(-0.51)
AFGR	-0.00390***	-0.00357***	-0.00161*	-0.00364***	0.00013	-0.000946***	-0.00061	-0.000194
	(-15.18)	(-14.10)	(-2.19)	(-13.42)	(-0.22)	(-3.85)	(-0.62)	(-0.51)
Unemployed	0.00652***	0.00441***	0.00136	0.00404***	0.00517	0.0000645	0.00738	-0.00182
	(5.58)	(3.79)	(0.34)	(3.32)	(1.44)	(0.06)	(1.68)	(-0.90)
Singleparent	0.00180***	0.00253***	0.00180*	0.00251***	0.000718	0.00128***	0.00133*	0.00168**
	(6.88)	(9.5)	(2.46)	(8.78)	(1.11)	(4.16)	(3.02)	(4.47)
Pm-days	0.00769***	0.00772***	0.00921***	0.00666***	0.00140**	0.000838	0.000784	0.000671
	(8.96)	(9.23)	(4.9)	(7.75)	(2.64)	(1.25)	(1.4)	(0.98)
Region		0.119***						
		(13.44)						
Less18					-0.00962***	-0.00653***	-0.0126*	-0.00896***
					(-4.49)	(-6.61)	(-2.48)	(-5.29)
Female					0.00465	0.00845***	0.00777	0.00826***
					(0.91)	(7.55)	(1.42)	(4.91)
Rural					-0.00138***	0.000565***	-0.00103*	0.000536**
					(-5.94)	(5.54)	(-2.84)	(3.65)
Hispanic					0.00207*	0.000703**	0.00268	0.00141***
					(2.41)	(3.06)	(1.67)	(6.43)
Black					0.00695***	0.00647***	0.00595**	0.00603***
					(11.12)	(33.92)	(4.07)	(11.27)
Year					-0.0189*	-0.00381	-0.0286*	-0.00479
					(-2.27)	(-0.79)	(-2.42)	(-0.90)
N	3788	3788	698	3090	698	3090	698	3090
R^2	0.527	0.549	0.316	0.486	0.589	0.65	0.499	0.504
$Adj-R^2$	0.526	0.547	0.308	0.485	0.581	0.648	0.489	0.501

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *T-statistics in parentheses*

APPENDIX F: Standardized Beta coefficients

Variables	$YPLL_{75}$		PUD		MUD		LBW	
	NE	S	NE	S	NE	S	NE	S
Obese	0.386	0.336	0.232	0.262	0.219	0.201	0.208	0.123
Teenbirth							0.162	0.154
Uninsured	-0.147	-0.114	-0.092	-0.14	-0.169	-0.081	-0.082	-0.102
PCP	0.016	0.018	-0.116	-0.108	-0.156	-0.106	-0.104	0.032
MHP	-0.098	-0.084			-0.065	0.003		
ACSC	0.173	0.18	0.222	0.104				
HBA1C	-0.07	-0.107						
AFGR	-0.074	-0.094	-0.123	-0.069	-0.088	-0.103	0.007	-0.055
Unemployed	0.133	0.026	0.002	0.148	0.009	0.107	0.069	0.001
Singleparent	0.247	0.195	0.366	0.074	0.392	0.062	0.056	0.094
Ozone-days	0.044	-0.086	0.056	-0.066	0.123	-0.019		
Pm-days							0.043	0.014
less18							-0.135	-0.1
Over65	0.306	0.133	0.113	0.071	0.17	0.061		
Female	0.093	-0.001	0.106	-0.014	-0.048	0.028	0.038	0.105
Rural	0.212	0.028	0.048	0.055	-0.024	-0.069	-0.27	0.08
Hispanic	0	-0.071	0.149	-0.022	0.016	-0.11	0.088	0.055
Black	0.354	0.057	-0.226	-0.297	-0.086	-0.301	0.443	0.586
Year	-0.376	-0.166	-0.268	-0.127	-0.312	-0.085	-0.106	-0.015
N	706	3085	696	2847	696	2864	698	3090

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

T-statistics in parentheses

APPENDIX G: Neumark Two-Fold Decompositions

	$YPLL_{75}$	*MUD*	*PUD*	*LBW*
Northeast	8.774***	1.230***	1.223***	1.989***
	(1193.88)	(192.71)	(176.70)	(366.62)
South	9.169***	1.408***	1.287***	2.219***
	(2300.88)	(329.17)	(268.73)	(611.04)
Difference	-0.395***	-0.178***	-0.0636***	-0.230***
	(-47.21)	(-23.11)	(-7.55)	(-35.21)
Explained Portion	-0.152***	-0.0411***	-0.00719	-0.142***
	(-15.69)	(-3.61)	(-0.54)	(-18.47)
Unexplained Portion	-0.243***	-0.136***	-0.0564***	-0.0882***
	(-24.92)	(-11.10)	(-3.88)	(-11.94)
N	3791	3543	3560	3788

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$; *t-Statistics in parentheses*

The Neumark (1988) decomposition is based on estimates from a pooled regression over the 2 regions.

APPENDIX H

We adopt the formulation of the Gale-Nikaido (1965) theorem in Friedman (1990, p. 86)[9]

Theorem 1 *Gale-Nikaido [1965] Univalence Theorem : Let $f(x)$ be a function from a convex set $X \subset \mathbb{R}^m$ to $\mathbb{R}^m$. If the Jacobian of f is negative quasi-definite for all $x \in X$, then f is one to one.*

To establish existence we need derive conditions under which the Jacobian in Equation (8) in the text is negative quasi-definite. For convenience we reproduce Equation (8) here:

$$J = \begin{pmatrix} \alpha_1 + \beta_1 & \beta_1 & \cdots & \beta_1 \\ \beta_2 & \alpha_2 + \beta_2 & \cdots & \beta_2 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_n & \beta n & \cdots & \alpha_n + \beta_n \end{pmatrix} \tag{A.2}$$

where

$$\alpha_i = E_\theta[U^i_{ee} - \theta d' U^i_{eq}] \tag{A.3}$$

$$\beta_i = E_\theta[-\theta d' U^i_{eq} - \theta d'' U^i_q + (\theta d')^2 U^i_{qq}] \tag{A.4}$$

9. For other versions of the theorem see Parthasarathy (1983) and Sydsæter, Strøm, & Berck (2005, pages 41 and 42).

A matrix is negative quasidefinite if the sum of the matrix and its transpose is negative definite [Friedman (1990, p. 85)]. Now construct

$$J+J^t = \begin{pmatrix} 2(\alpha_1+\beta_1) & \beta_1+\beta_2 & \cdots & \beta_1+\beta_n \\ \beta_1+\beta_2 & 2(\alpha_2+\beta_2) & \cdots & \beta_2+\beta_n \\ \vdots & \vdots & \ddots & \vdots \\ \beta_1+\beta_n & \beta_2+\beta n & \cdots & 2(\alpha_n+\beta_n) \end{pmatrix} \tag{A.5}$$

Since the equilibrium must be symmetric we can write $\alpha_i = \alpha$ and $\beta_i = \beta$ so that Equation (A.4) becomes

$$J+J^t = \begin{pmatrix} 2(\alpha+\beta) & 2\beta & \cdots & 2\beta \\ 2\beta & 2(\alpha+\beta) & \cdots & 2\beta \\ \vdots & \vdots & \ddots & \vdots \\ 2\beta & 2\beta & \cdots & 2(\alpha+\beta) \end{pmatrix} \tag{A.6}$$

We want this to be negative definite, which requires its principal minors to alternative in alternate in sign, negative, positive, negative, etc. Notice that the principal minor of order $j = 1, 2, \ldots, n$ is

$$|D_j| = (2\beta)^j \begin{vmatrix} \frac{\alpha}{\beta}+1 & 1 & \cdots & 1 \\ 1 & \frac{\alpha}{\beta}+1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & \frac{\alpha}{\beta}+1 \end{vmatrix} \tag{A.7}$$

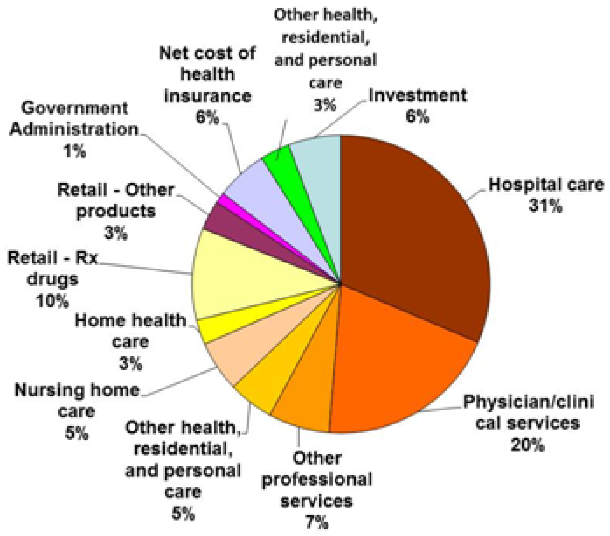
Now apply Result 20.11 of Sydsæter, Strøm, and Berck (2005, p. 143) to find

$$|D_j| = (2\alpha)^j[1 + j\frac{\beta}{\alpha}] \tag{A.8}$$

Negative definiteness therefore requires $\alpha^{j-1}(\alpha + j\beta)$ to alternate in sign, negative, positive, negative, for $j = 1, 2, \ldots, n$; which yields Proposition 1.

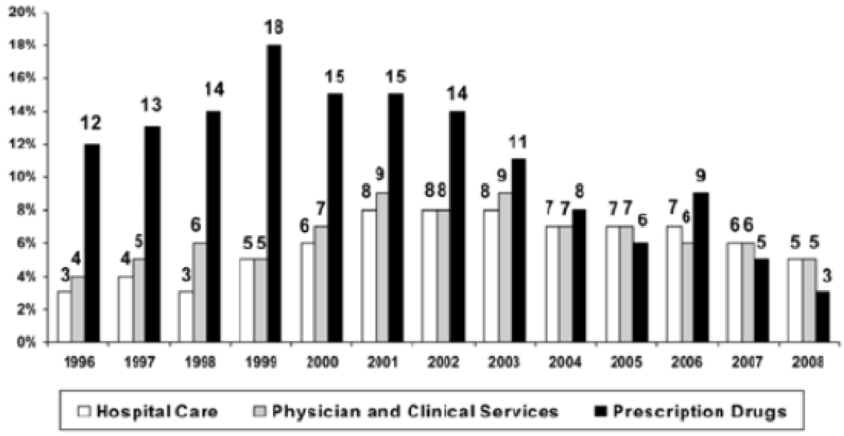
The principal minors will only alternate in sign if and only if $\alpha < 0$. They will alternate in sign in the proper sequence (negative, positive, negative, . . .) if and only $\alpha + j\beta$.

APPENDIX I: National Health Expenditures



Source: Martin et al., 2012

APPENDIX J: Annual Change in Selected National Health Expenditures (96-08)



Source: Kaiser Family Foundation, May 2010

APPENDIX K: Convergence clubs in prescription drugs expenditures

Clubs	**States**
High	AL, CT, DE, FL, KY, ME, MA, NJ, NY, NC, PA, RI, SC, TN, WV
Average	Remaining states
Average-Low	CO, NM
Low	AZ, CA, HI, ID, MT, OR, SD, TX, UT, WA, WY

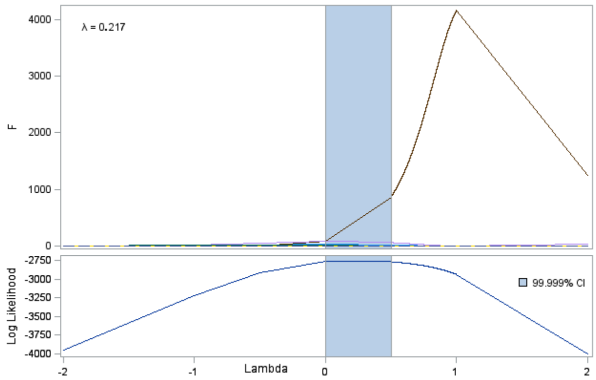
Source: Panopoulou and Pantelidis (2012)

APPENDIX L: Region Specific Box-Cox Procedure Estimation of Lambda

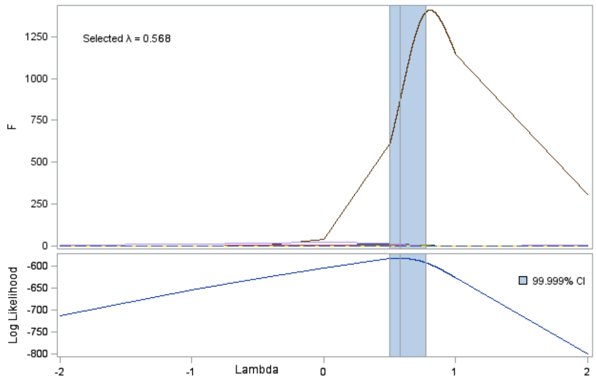
	λ	**Std. Err.**	**P>z**	**95% Conf. Interval**
Pooled Model	0.21689	0.03936	0	[0.13975, 0.29403]
High Spenders	0.56794	0.05008	0	[0.46978, 0.66610]
Average Spenders	0.69565	0.05326	0	[0.59127, 0.80003]
Low Spenders	0.08681	0.05643	0.124	[-0.0238, 0.19740]

APPENDIX M: Box-Cox Analysis of Prescription Drug Consumption

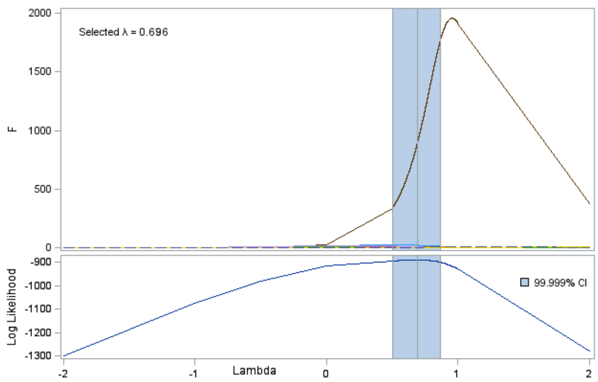
(a) Pooled



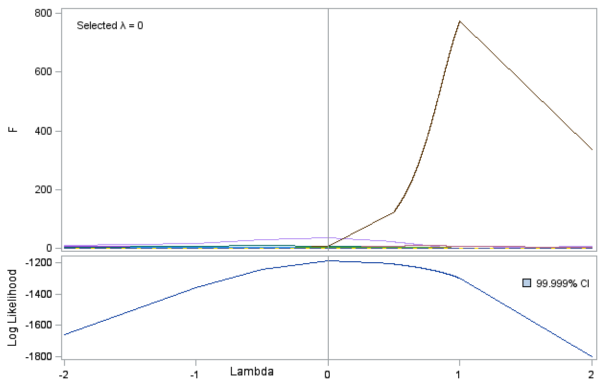
(b) High



(c) Average

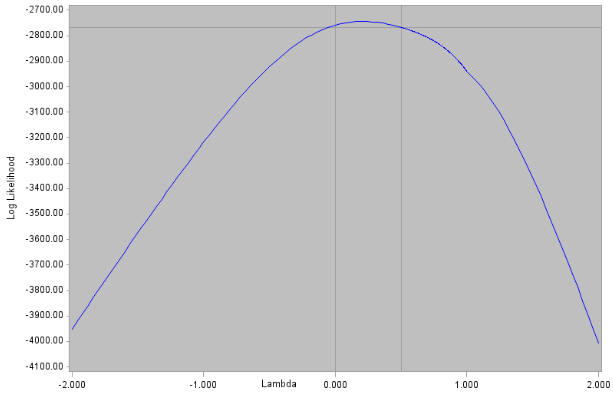


(d) Low

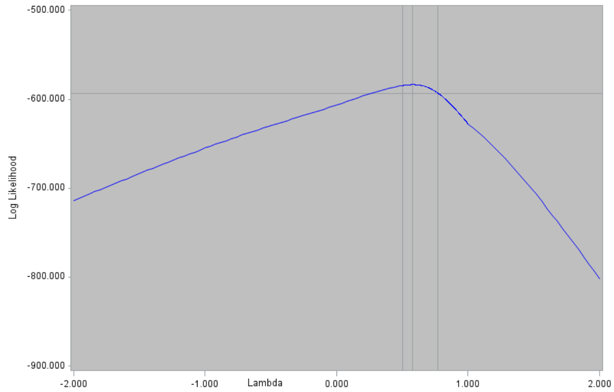


APPENDIX N: Log-Likelihood Profile for Different Lambda

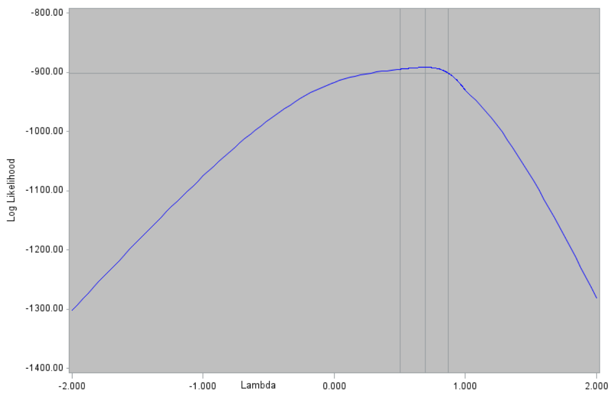
(a) Pooled



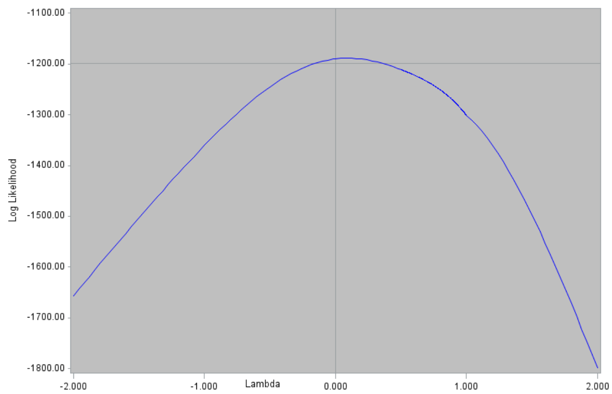
(b) High



(c) Average

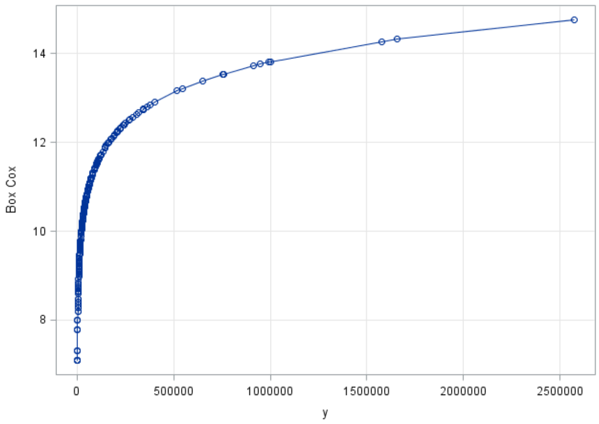


(d) Low

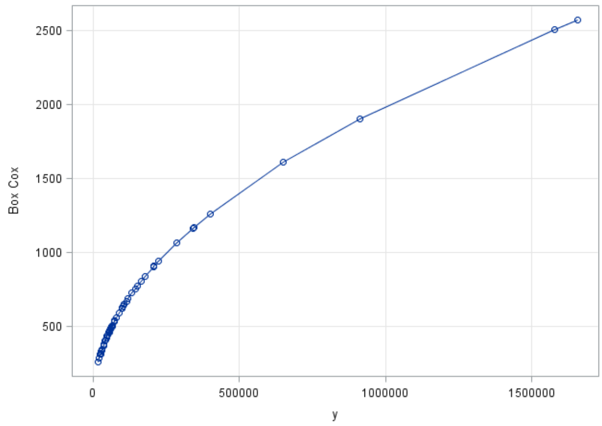


APPENDIX O: Scatter Plot of the Box-Cox Transformed to the Original variables

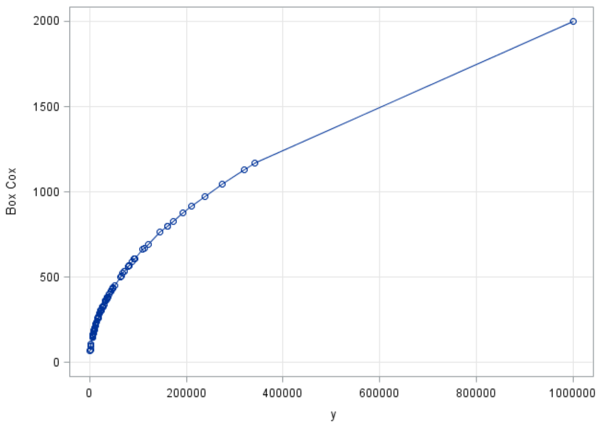
(a) Pooled



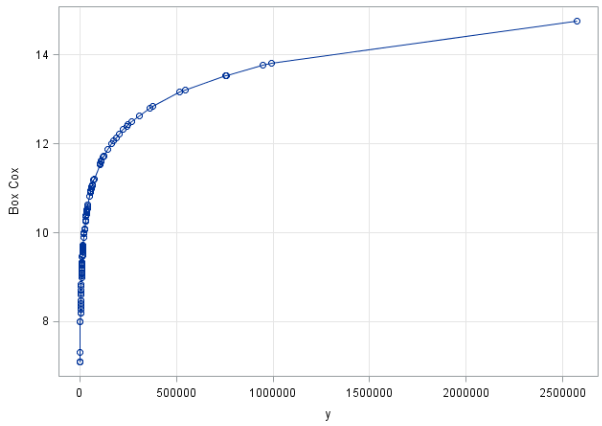
(b) High



(c) Average

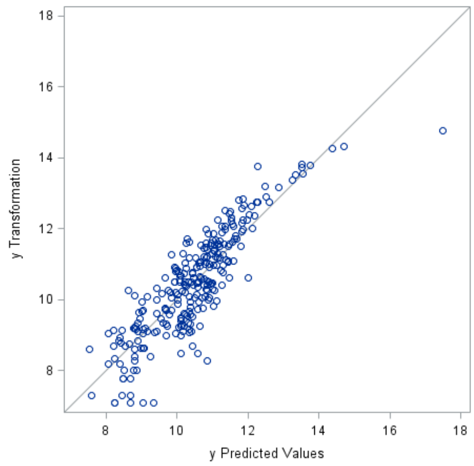


(d) Low

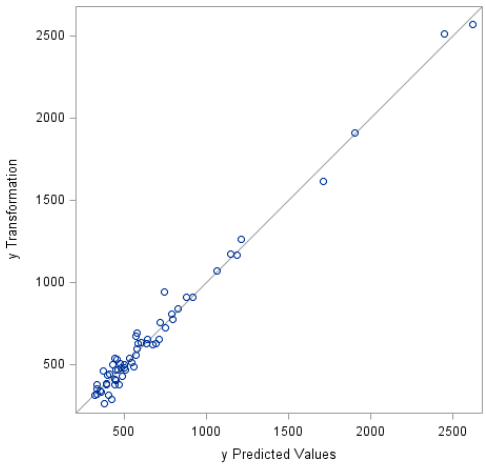


APPENDIX P: Scatter Plot of the Box-Cox Transformed to the Predicted values

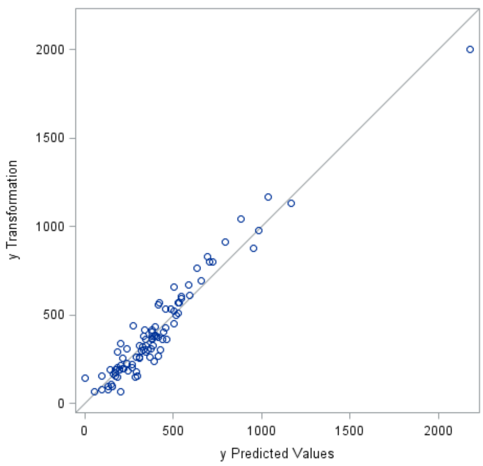
(a) Pooled



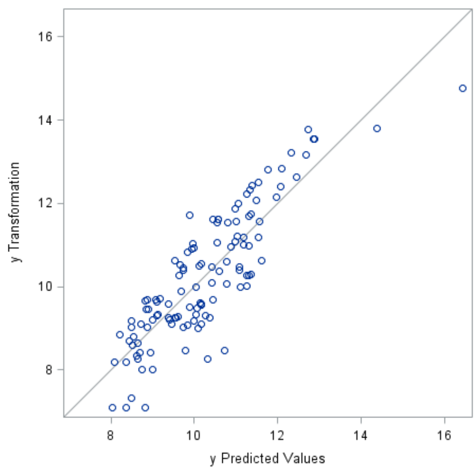
(b) High



(c) Average



(d) Low



APPENDIX Q: Marginal Effects Computation

Suppose X_i is the explanatory variable of interest, β_i the estimated coefficient parameter, and $Y^{(\lambda)}$ the transform dependent variable.

The marginal effect of X_i is given by:

$$\frac{\partial Y}{\partial X_i} = \beta_i[\lambda Y^{(\lambda)} + 1]^{\frac{1-\lambda}{\lambda}} = \beta_i \tilde{Y} \tag{A.9}$$

The following table summarizes the marginal effects for the significant variables the High and Low Spending States

Margibal Effects of of Selected Significant Variables on Prescription Drugs Consumed

	High Spenders	**Average Spenders**
λ	0.567942	0.69565
$Y^{(\lambda)}$	1370.788	2604.287
$\tilde{Y}$	158.4679	26.6397
Fair-Poor		-1295.49
PCP	252.28	
Pharmacies	4422.84	4739.20
PSED		611.11
Black		-640.42
Hispanic		-620.705
Rural	-935.592	-261.92
AR		27553.44

APPENDIX Q: Income Elasticity Computation

The income elasticities for prescription drugs consumption is computed as follows for the high and average spending regions:

- First, using the mean observation values for each region, we compute the Box-Cox predicted prescription drugs consumption level, $\bar{Y}$
- Second, given $\bar{Y}$, the income elasticity is given by

$$e_{Y/Inc} = \frac{\partial Y}{\partial Inc} \times \frac{\bar{Inc}}{\bar{Y}} \tag{A.10}$$

  with *Inc* the median household income level

The predicted prescription drugs consumption can be rewritten as:

$$Y^{(\lambda)} = \beta Inc + \theta Inc^2 + Z \tag{A.11}$$

And

$$e_{Y/Inc} = [\beta + 2\theta \bar{Inc}]\tilde{Y} \times \frac{\bar{Inc}}{\bar{Y}} \tag{A.12}$$

For the low spending region, the income elasticity is given by :

$$e_{Y/Inc} = [\beta + 2\theta \bar{Inc}]\bar{Inc} \tag{A.13}$$

Computed Income Elasticity by region

	Pooled Model	**High Spenders**	**Average Spenders**	**Low Spenders**
λ	0.216887	0.567942	0.69565	0
$\tilde{Y}$	4376.414	158.468	26.639	
$\bar{Y}$	89241.4117	121,708.79	52,263.14	99,996.41
β	0.000682	0.0359	-0.094	0.0000112
θ	-5.56E-09	-3.31E-07	8.770E-07	-8.71E-11
$I\bar{n}c$	40,414.33	37,784.04	39,349.57	43,006.06
Elasticity	**0.461**	**0.535**	**-0.501**	**0.482**

APPENDIX R: Standardize- Beta Coefficients

	Pooled Model	**High Spenders**	**Average Spenders**	**Low Spenders**
	Pooled Data	High Spenders	Average Spenders	Low Spenders
Obese	-0.010	-0.022	0.018	0.028
Smokers	0.090*	-0.011	0.019	0.263**
Fair-Poor	0.005	0.006	-0.097**	-0.262*
PCP	0.090**	0.077***	0.015	0.160**
Uninsured	0.094	0.052	-0.077	0.040
Pharmacies	0.493***	0.858***	0.846***	0.212
PSED	0.004	0.038	0.103*	-0.036
Income	0.360	0.270*	-0.256	0.057
GINI	-0.005	-0.015	0.052	-0.092
Black	-0.084**	-0.041	-0.126**	0.112
Hispanic	-0.047	-0.035	-0.038	0.054
P65	-0.163***	-0.005	-0.160*	-0.114
Female	0.073*	0.006	0.017	0.062
Rural	-0.405***	-0.127**	-0.093*	-0.484***
High Spenders	0.197***			
Average Spenders	0.083*			
East TN		0.019		
Middle TN		0.023		
AR			0.174*	
ID				-0.128
SD				-0.268**

Note: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$