Distribution Agreement

Signature:

______________________________ _______________
Yu-Hua Chen Date

The Joint Effect of Restaurant Trans Fat Bans and Menu Labeling Laws on the Prevalence of Hypertension and Coronary Heart Disease

By

Yu-Hua Chen

Thesis Committee Chair: Sara J. Markowitz, Ph.D.,
The Graduate School and University Center of the City University of New York

An abstract of a master thesis
submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Arts
in Economics
2014

Abstract

The Joint Effect of Restaurant Trans Fat Bans and Menu Labeling Laws on the Prevalence of Hypertension and Coronary Heart Disease
By Yu-Hua Chen

Starting in 2007, several city and state governments have implemented restaurant related dietary policies to the overall health outcomes of their constituents. This paper intends to estimate the average treatment effect of the joint treatment of trans fat bans and menu labeling law on both aggregate measure health outcomes and individual-level health outcomes. To overcome the problem of policy overlapping and hidden selection bias, I apply propensity score method for the first stage estimation and inverse probability weighting estimator for average treatment effect on the aggregate prevalence of hypertension and coronary heart disease. I find trans fat ban decreases the prevalence of coronary heart disease by 2 percentage point. The average treatment effect of multiple overlapping policies decreases the prevalence of coronary heart disease by 1.4 percentage point. The average treatment effect on the treated of multiple overlapping policies decreases the prevalence of coronary heart disease by 1.59 percentage point. I also use individual-level data to estimate the effect of Baltimore trans fat ban on the prevalence of hypertension. I apply Difference-in-Differences method and improve the reliability of inference by wild bootstrap procedures, I find Baltimore trans fat ban decreases the prevalence of hypertension among the elderly by 4.65 percentage point in linear probability model.

The Joint Effect of Restaurant Trans Fat Bans and Menu Labeling Laws on the Prevalence of Hypertension and Coronary Heart Disease

By

Yu-Hua Chen

Thesis Committee Chair: Sara Markowitz, Ph.D.

A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of
Master of Arts
in Department of Economics
2014

The Joint Effect of Restaurant Trans Fat Ban and Menu Labeling Law on the Prevalence of Hypertension and Coronary Heart Disease

Yu-Hua Chen

Abstract

Starting in 2007, several city and state governments have implemented restaurant related dietary policies to the overall health outcomes of their constituents. This paper intends to estimate the average treatment effect of the joint treatment of trans fat bans and menu labeling law on both aggregate measure health outcomes and individual-level health outcomes. To overcome the problem of policy overlapping and hidden selection bias, I apply propensity score method for the first stage estimation and inverse probability weighting estimator for average treatment effect on the aggregate prevalence of hypertension and coronary heart disease. We find trans fat ban decreases the prevalence of coronary heart disease by 2 percentage point. The average treatment effect of multiple overlapping policies slightly decreases the prevalence of coronary heart disease by 1.4 percentage point. The average treatment effect on the treated of multiple overlapping policies decreases the prevalence of coronary heart disease by 1.59 percentage point. I also use individual-level data to estimate the effect of Baltimore trans fat ban on the prevalence of hypertension. I apply difference-in-differences method and improve the reliability of inference by wild bootstrap procedures, I find Baltimore trans fat ban decreases the prevalence of hypertension among the elderly by 4.65 percentage point in linear probability model.

List of Tables

1 Introduction

The effectiveness of restaurant dietary policy is the main focus of this paper. This paper investigates the combined effect of menu labeling law and trans fat ban on health outcomes. To obtain unbiased estimates of the effect of trans fat ban and menu labeling law, we need to overcome two identification challenges.

1. Multiple treatments: Menu labeling law requires restaurants to declare calorie counts on their menus, while restaurant trans fat bans aim to lowering people's trans fat intake from restaurant meals. Both kind of law aim to improve people's dietary intake. Table 1 shows the timeline of trans fat bans and menu labeling law in the U.S. Most of the cities and states listed in table 1 have both trans fat ban and menu labeling law implemented. The time gap between the implementations of the

two policies is often shorter than two years. The identification difficulty here lies in credibly distinguishing between the respective treatment effects between trans fat ban and menu labeling law.

2. Selection-on-unobservables: City or state government may decide to have restaurant dietary policies due to unobserved characteristics which are correlated with health outcome variables. It is important to control the variables that influences outcome variables and treatment assignment mechanism. The difference between control group and treatment group can be address by understanding the process of policies. It is thus necessary and important to understand the policy-making process and the variables that determine the health policy. Once we take these identification problems into account, we can construct a balanced treatment group and control group, and make a more justifiable estimation of treatment effects.

I adopt two econometric techniques to identify the treatment effects: (1) the propensity score method and (2) the inverse probability weighting estimator. Both methods are applied to correct the endogenous treatment assignment mechanism for each city and state. The first stage of the estimation is to generate propensity scores for each sample unit. We use propensity scores to determine the similarity among cities and to further estimate the effects of trans fat ban and menu labeling law. By comparing the health outcomes of the control groups and treatment groups, we can correctly attribute changes in health outcome to the health policies. Inverse probability weighting uses the propensity score to weight the sample and correct the endogenouse selection problem. The model set up of this paper is established from the works of these two papers: Lechner (2001) and Bradley (2012). Lechner extends the propensity score matching method from a single treatment to multiple treatments for different heterogeneous labor programs. Bradley(2012) estimates the joint evaluation of two overlapping education policies and provides a basic econometric framework for estimating the effects of multiple overlapping policies.

This paper contributes to the literature by estimating the joint effect of local trans fat ban and menu labeling law on health outcomes. The effect of the restaurant dietary policies on health outcomes has not been studied deeply to the author's understanding. Angell *et al.* (2012) conduct a pre-post study to investigate changes in the amount of trans fat intake in New York City after its trans fat ban went into effect. Their method is to randomly collect purchase receipts before and after the ban and they find the average intake of trans fat per purchase decreases 2.4 grams per meal after New York City trans fat ban. Vesper *et al.* (2012) find that mandatory TFA labeling in the United States is associated with a reduction in LDL cholesterol level and an increase in HDL cholesterol levels among non-Hispanic adults.

The most relevant research in the literature is in two working papers by Restrepo and Rieger (2014). They estimate the effect of NYC trans fat ban and NYC menu labeling law in two separate papers. One analyzes the impact of the NYC trans fat ban on cardiovascular disease mortality rate. Their results shows NYC trans fat bans lower CVD mortality rates by 4%. Another working paper by Restrepo (2014) studies the impact of NYC mandatory calorie labeling on body weight. Restrepo finds that NYC menu labeling law has a larger impact in the upper half of the BMI distribution.

My paper differs from Restrepo and Rieger (2014) in these respects: (1)I covers all the cities and states in the U.S that have currently implemented with trans fat bans and menu labeling law (as of 2014), while Restrepo's paper analyzes only New York City. (2) I construct a multi-valued treatments model to estimate the joint effect of concurrent trans fat bans and menu labeling law. Since these two policies are highly correlated, it is not feasible to analyze their impacts separately. (3) I use the propensity score method to construct balanced control groups and treatment groups while Restrepo's paper does not account for this confounding issue.

To support the estimation results of the joint treatment effect policy, this paper uses city of Baltimore as a case study for the treatment effect of a trans fat ban. Baltimore is the only large city in the U.S where no menu labeling law is enforced. In the section of Baltimore trans fat ban, the outcome variable is individual health outcome and sample unit is also individuals. I estimate the effect of Baltimore trans fat ban using the difference-in-differences method, and I improve the reliability of inference by wild bootstrap procedures. By applying the data from HCUP database's Nationwide Inpatient Sample (NIS) from 2004 to 2011, the estimated effect of trans fat ban is statistically significant for the adult group and the elderly group for the model without controlling hospital fixed effect. For the elderly group, the trans fat ban decreases the prevalence of hypertension by 4.65 percentage point. In the hospital fixed effect model, the effect of the trans fat ban increases slightly 0.07 percentage point for both adult groups and elderly groups.

2 Background

2.1 Adverse effect of trans fat

Artificial *trans*-fatty acids is an artery-clogging fat produced by adding hydrogen to vegetable oil through a process called hydrogenation. It is commonly used in commercial food processing to keep the stability of deep frying oil and extend the shelf life of foods. The recommended daily trans fat consumption for individuals is less than 2 grams per day by the U.S. dietary guidelines. However, according to the information of U.S. Food and Drug Administration (FDA) in 2003, the average daily trans fat intake for American adults is 5.8 grams.

Trans-fatty acids has been known to have an adverse effect on increasing the risk factor of coronary heart diseases (CHD). The intake of trans fat results in adverse lipid effect by driving up the level of low-density lipoprotein (LDL) cholesterol and lowering down the level of high-density lipoprotein (HDL) cholesterol. High level of LDL cholesterol leads to arteries hardening and hypertension. Medical evidence confirms that consuming trans-fatty acids from partially hydrogenated oils adversely affects multiple cardiovascular risk factors, resulting in cardiovascular diseases. According to four prospective cohort studies, 2% increase in energy intake from trans fat (4 grams per day) is associated with a 23% higher incidence of myocardial infarction and CHD death (Micha, R, Mozaffarian 2008).

The danger of TFA intake has become an important health topic. The American Heart Association recommends that the daily TFA intake of adults should be as low as possible, ideally amounting to less than 1% of total daily caloric intake. Medical research has indicated that the consumption of artificial TFAs increases the level of LDL cholesterol in the blood and raises one's risk factor for coronary heart disease. Several cities in the U.S., including New York, Philadelphia, Boston, and Baltimore, have passed trans-fat bans for restaurants. These bans restrict restaurants from serving meals containing more than 0.05 grams of artificial TFAs. Most epidemiology research focuses only on the adverse health effects of TFA intake, while the actual effect of trans-fat bans on public health remains an unanswered empirical question. The purpose of this paper is to use the HCUP Nationwide Inpatient Sample to investigate the effect of local trans-fat bans on health outcomes.

The effect of a trans-fat ban on health outcomes can be approximately forecast through the following steps. The mechanism connecting trans-fat bans with rates of heart diseases can be explained as occurring through this channel: the ban decreases the amount of trans-fat consumed in the restaurant; the reduction in trans-fat intake improves people's levels of HDL and

LDL cholesterol; and this change decreases people's incidence of heart disease. According to Angell's 2012 study, the average decrease after New York's ban was 2.4 grams of TFA per meal. This reduction in TFA intake amounts to around 1% of a person's total daily caloric intake, given that the average daily intake is 2000 calories. Following the result of the control-trialed study, over the course of a three-week diet, replacing 1% of a person's total energy intake with trans-fatty acids decreased their HDL cholesterol level by 0.017 mmol/L and increased their LDL cholesterol by 0.037 mmol/L (Ronald and Katan, 1990). On the assumption that the relationship between trans-fat intake and LDL-reduction is linear, the total LDL cholesterol reduction per year after the trans-fat ban would be around 0.44 mmol/L, and the total HDL increase around 0.204 mmol/L. Combining this with the results of the medical paper, we can expect that the annual rate of fatal coronary heart disease would diminish by 7.3% after the trans-fat ban (Malcolm R. Wald, 1994). The predicted effect of the trans-fat ban might be larger than the empirical result, though, because the exact effect of the ban would differ among age groups and income groups.

Although most medical research has focused on the adverse effects of TFAs on people's risk for CHD events, the health outcome chosen in this paper is hypertension for the following two reasons: First, the risk factors for coronary heart disease are measured in the 10- or 20-year term. The effective period of the trans-fat ban in Baltimore is still too short to be used in any such investigation of changes in CHD events. Second, hypertension is one of the risk factors most highly correlated with the occurrence of CHD. One prospective-cohort study of middle-aged and older women found a positive association between trans-fat intake and the risk of hypertension (Wang et al., 2010). Furthermore, changes to dietary patterns take only about three to eight weeks to have an effect on hypertension; we can thus expect to see a quicker effect here. According to the report Heart Disease and Stroke Statistics 2013, 33% of U.S. adults have hypertension; hence the association between trans-fat bans and hypertension is an important topic to study.

2.2 Trans fat policy in the U.S.

There are two kinds of health policies related to TFAs in the U.S: (1) mandatory trans-fat-labeling laws, and (2) trans-fat bans. (1) The federal labeling law was enacted by the Food and Drug Administration (FDA) in 2006. The FDA requires food manufacturers to state the amount of trans fats a food product contains as part of the food's nutritional information. This law provides extra nutritional information to consumers and allows them to purchase trans-fat-free products. (2) Trans-fat bans are different from these, and focus instead on removing TFAs from restaurant meals. The advantage of trans-fat bans is that they ensure the safety of food intake even when people dine out. Where consumers cannot choose the precise contents of their meals, it is important to protect them from dangerous ingredients.

Table 1 shows a timeline of cities with trans-fat bans. The first trans-fat-free city in the U.S. was Tiburon, California, in which all restaurants voluntarily agreed to cook with trans-fat-free oils. Montgomery County, Maryland, put in place the first countywide trans-fat ban. New York was the first city to have a city-wide ban, and in a trend of local trans-fat bans, many other municipal health departments have followed New York. California was by a wide margin the first state to enact a statewide trans-fat ban. Table 1 also gives a timeline of menu-labeling laws for each city.

In the city targeted in this paper, Baltimore, the Health Department amended the Health Code in March 2008 to prohibit food facilities from serving dishes that contained more than 0.5 grams of TFA per serving. The ban went into effect in September 2009. In the Baltimore Health Code 6-507, food containing trans fats is stipulated to be any food containing vegetable shortening, margarine, or any kind of partially hydrogenated vegetable oil. If a food service facility violates this ban, the commissioner may issue an order of suspension.

2.2 Menu Labeling Law

Menu labeling laws require restaurants chains that have at least 20 U.S. locations to declare the caloric values of the foods on their menus. This information could help consumers recognize high-calorie food avoid excessive caloric intake. In May of 2007, New York became the first city in the U.S. to enact a menu-labeling law. Boston, Philadelphia, and several other counties enacted similar regulations in 2009 and 2010. Beginning with California in 2009, many states have enacted statewide menu-labeling laws. These include

Table 1: List of U.S cities with trans fat ban and menu labeling law

City	Trans Fat Policy	Menu labeling law
New York City,NY	July, 2007 - oil	May, 2008
	July, 2008 - all food	
Philadelphia, PA	Sep, 2007	Apr, 2010
Puerto Rico	Jan, 2008	
Brookline, MA	Nov, 2008	Nov, 2010
Nassau County, NY	Apr, 2008	
Westchester County, NY	Apr, 2008	May, 2009
Boston, MA	Sep, 2008 - oil	Nov, 2010
	Mar, 2009 - all food	
Baltimore, MD	Sep, 2009	
Cambridge, MA	July, 2009	Nov, 2010
California	Jan, 2010 - oil	July, 2009
	Jan, 2011 - all food	Jan, 2011
Suffolk County, NY	Oct, 2010- oil	Feb, 2009
	Oct, 2011- all food	
Maine		May,2010
Oregon		Jan,2010
Massachusetts		Nov,2010

Oregon, Maine, and Massachusetts. In 2010, the U.S. Congress passed the Patient Protection and Affordable Care Act (ACA), which required menu-labeling in all restaurants chains with 20 or more locations in the country. The U.S. Food and Drug Administration (FDA) proposed a nationwide regulation for menu-labeling in 2011, but the precise date of enaction is still under discussion. Recent studies on menu-labeling laws have focused on consumer purchasing behaviors. Bollinger et al. (2011) used consumer purchasing data from Starbucks to study the impact of New York's menu-labeling law; they found that the average calories per transaction fell by 6% following the law's introduction. Krieger et.al (2013) conducted a single-community, pre–post–post cross-sectional study to determine the impact of a menu-labeling law in King County, Washington. Their method was to collect customers' receipts and to conduct interviews with customers. Their results indicated that after 18 months of menu labeling, the average calories per transaction had decreased from 908.5 to 870.4.

PART 1 Treatment effect from aggregate health outcome.

3 Empirical methodology

3.1 Model specification for aggregate panel data

The goal of this paper is to investigate the interactive effect of menu-labeling laws and trans-fat bans on health outcomes. To obtain the unbiased estimates of the effects of trans-fat bans and menu-labeling laws, we need to overcome the following identification challenges. (1) Multiple treatments: Both trans-fat bans and menu-labeling laws aim to improve people's dietary intake. Most cities and states in table 1 have implemented both a trans-fat ban and a menu-labeling law. The gap in time between the implementation of the two policies is often shorter than two years. The difficulty in identification arises when trying to distinguish credibly the treatment effects of trans-fat bans from those of menu-labeling laws. (2) Hidden selection bias: The assumption of exogeneity would not hold if the policy decision to implement a trans-fat ban and a menu-labeling law were correlated with unobserved characteristics.

3.1.1 Multiple overlapping treatments and multinomial model:

To address the first identification difficulty, overlapping trans fat ban and menu labeling law, I follow the multiple-treatment analysis framework as in Bradley and Giuseppe (2012) to create a multinomial category for multiple overlapping policies. There are total four possible status for the treatment category. The first types is "No trans fat ban nor menu labeling law". The second types is "The city only with trans fat ban" The third types is "City only with menu labeling law" and the last one is the city with both trans fat ban and menu labeling law. The following tables shows how these four treatment categories are defined. With the multinomial categories, I could identify the relative effect of each policy by comparing the estimates under different treatments. The differences in periods and cities in the sample also provide enough variations to enable us to identify the relative treatment.

Treatment Category	Multinomial Category	Example
No policy at all	0	Most of the U.S cities
Only trans fat ban	1	Baltimore
Only menu labeling	2	Maine, Oregon
Trans fat + Menu labeling	3	NYC, Boston

3.1.2 Endogenous assignment mechanism and propensity score:

The method for correcting the endogenous selection into the treatment is to generate a propensity score for each sample in the first stage. The identification of the treatment effect relies upon conditional independence assumption, which means the potential health outcome should be independent from the assignment mechanism given the observed covariates. As mentioned before, the implementation of trans fat ban and menu labeling law might correlate with the high prevalence of dietary disease in the given city due to unobserved characteristics. It is important to understand the process of the policymaking and the determinant variables behind the health policy. Once we take into account for these identification problem, we can construct a balanced treatment group and control group, and obtain a more justifiable estimation of treatment effect.

This paper applies propensity score method to include the variables that might influence the assignment mechanism of treatment. One major advantage of propensity score is to reduce the dimension of covariates and to summarize the information in the observerable characteristics without violating the conditional independence assumption. Another advantages of propensity score is to construct a counterfactual group that has similar characteristics to the treatment group. We use propensity score to determine the similarity among cities and further estimate the effect of trans fat ban and menu labeling law. By comparing the health outcomes of the well-selected control groups and treatment groups, the effect of the change in health outcome can be attributed to the health policy.

Propensity score is defined as the probability that a city in a given period of time has the implementation of trans fat ban or menu labeling law. Propensity score is a function of a set of city characteristics and health outcomes. Each city has a different probability of participating the trans fat ban and menu labeling law. As mentioned before, menu labeling law and trans fat ban are multiple treatments to the health outcome. There are total four treatment categories for the policies. I estimate the propensity score by the following multinomial Logit model.

$$Pr(T_i = j|X_i) = \frac{\exp(X_i\beta)}{1 + \sum \exp(X_i\beta)}$$

where $\Pr(T_i{=}j)$ is the probability that a city in a given period of time have either trans fat ban or menu labeling law or no policy at all. X_i represents the time variant covariates that influence the formation of the policy.

Inverse Probability Weighting (IPW) estimator is first proposed by Rosenbaum and Rubin (1983) Hirano, Imbens, and Ridder (2003) extends the model of weighting by inverse of inverse of a nonparametric estimate of the propensity score. As Hirano notes in his 2003 paper, when the propensity score equals to the weighted function, the average treatment effect on the treated is a special case of weighted average treatment effect. The next equation shows the form of the Inverse probability weighting estimator derived by Hirano et.al (2003).

$$\hat{\tau}_{IPW} = \frac{\sum \frac{T_i Y_i}{P(X_i)}}{\sum \frac{T_i}{P(X_i)}} - \frac{\sum \frac{(1-T_i)Y_i}{1-P(X_i)}}{\sum \frac{1-T_i}{1-P(X_i)}}$$

where T_i represents the treatment variable, Y_i denotes outcome variable, and $P(x_i)$ is the propensity score given the observed covariates X_i. The average treatment effect of the joint effect is estimated by General Linear Model weighted by the inverse probability weighting estimator. The dependent variables in the model, the prevalence of the hypertension and heart disease, belong to the category of fraction response variable. From the table of summary statistics, the proportion of the hypertension population in all the sample lies between 0.28 to 0.4. The distribution of the data has the property of linear relationship so the generalized linear model is still suitable for the estimation. The average treatment effect is estimated by the following equation:

$$H_{ct} = \alpha_1 + \alpha_2 Treat_{ct} + +\beta_1' X_{ct} + YearQuarter_t + City_c + v_{ct}$$

where H_{ct} are the prevalence of hypertension and coronary heart disease respectivly in a city c for a given year quarter t , $Treat$ is a multinomial categorical variables for four types of treatment combinations . X is a vector of time-variant city characteristics covariates. $City_c$ is City fixed effect and $YearQuarter$ is year quarter fixed effect. v_{ijt} is a stochastic error term.

4 Data

The covariates used to estimate the propensity score belong to three categories. The first category is the time-variant geographic characteristics of a city, such as its annual population size, the proportion of elderly in its population, and the balance between genders in its population. The source of data for the population size is the annual estimates of the population of Metropolitan and Micropolitan Statistical Areas, released by the Population Division of the U.S. Census Bureau. The second category involves the socio-economic characteristics, including the per capita quarterly unemployment rate. The source for the data of per capita income by Metropolitan Statistical Areas is the Income Statistics Branch/HHES Division of the Censuses of Population and Housing. The third category is the health index of the citizens, generated from the Nation Inpatient Sample, which includes the quarter-yearly data on the prevalence of hypertension and coronary heart disease. I also include the prevalence of obesity when the data come from the Behavioral Risk Factor Surveillance System (BRFSS). All of the health-related covariates include lagged variables from one to three years. The factors related to the health index could help address the problem of endogeneity mentioned in the previous section. A city's characteristics can help identify the differences between a treatment city and a control group city.

In order to capture the change in health outcomes after the trans-fat ban, I use the inpatient data from the Healthcare Cost and Utilization Project (HCUP) of the Nationwide Inpatient Sample (NIS) from 2004 to 2012. The NIS contains more than seven million hospital stays from about 1,000 hospitals, which is sampled to a 20-percent-stratified sample of U.S. community hospitals per year. Each inpatient stay record in the NIS includes an ICD-9-

Table 2: Summary Statistics by treatment categories for aggregate data

	No Policy	Trans Fat Ban	Menu Labeling	Trans Fat Ban+ Menu Labeling	Total
	0	1	2	3	
Hypertension	0.254	0.291	0.203	0.267	0.255
	(0.0637)	(0.0277)	(0.0670)	(0.0504)	(0.0633)
Hypertension among Elderly	0.512	0.531	0.480	0.527	0.513
	(0.0677)	(0.0635)	(0.0729)	(0.0485)	(0.0672)
Coronary Heart Disease	0.106	0.0915	0.0762	0.0895	0.105
	(0.0532)	(0.0176)	(0.0319)	(0.0313)	(0.0519)
Coronary Heart Disease among Elderly	0.335	0.319	0.283	0.311	0.333
	(0.0809)	(0.0583)	(0.0928)	(0.0425)	(0.0799)
Obesity	0.255	0.258	0.241	0.232	0.254
	(0.0411)	(0.0298)	(0.0374)	(0.0274)	(0.0406)
Capita Income	39202.9	51424.3	44527.9	52453.6	40082.0
	(7135.5)	(3238.9)	(8373.2)	(6258.6)	(7723.2)
Population	1946234.0	6346298.9	3564519.5	8078611.7	2309902.0
	(2960429.5)	(5182526.8)	(3210241.8)	(6984118.3)	(3532270.5)
Quarterly Unemployment Rate	6.382	7.079	10.88	9.379	6.588
	(2.620)	(1.445)	(1.339)	(1.705)	(2.677)
Observations	1324	30	22	50	1324

mean coefficients; standard error in parentheses

CM, which provides information about the diagnosis of and procedures for a particular patient, and this allows the researcher to identify the prevalence of certain diseases over the years. The data includes not only the demographic characteristics of a patient, but also the associated hospital's geographic information, with the hospital's identifiers.

The definition of cardiovascular disease according to World Health Organization include coronary heart disease, cerebrovascular disease, peripheral arterial disease, rheumatic heart disease, congenital heart disease, deep vein thrombosis and pulmonary embolism. Among the categories of cardiovascular disease, medical research (Mozaffarian et.al 2006) indicates trans fat intake has strong association with coronary heart disease (CHD). I generate the indicator of coronary heart disease (CHD) and cardiovascular disease (CVD) from Nationawide Inpatient Sampe by the clinical classifications software (CCS). Coronary heart diseases is coded as "the Coronary atherosclerosis and other heart disease" in clinical classifications software.

The dependent variables of the aggregate health outcome are either the prevalence of hypertension or that of coronary heart disease. The outcome variable is aggregated quarter-yearly according to Metropolitan Statistical Area. The sample includes total 22 states and 40 cites. One potential problem raised here is that the unit of policy implementation includes different political divisions; some are statewide regulations,while some are municipal regulations. For the convenience of analysis, I have included the different regional levels in one sample so that I could gather more implemented treatment samples in my data.

5 Estimation Result for aggregate data

5.0.3 The result of first stage propensity score

Table 3 reports the result of a multinomial logit estimation for the propensity score. Dependent variables in the multinomial logit model is the four treatment categories: "No Policy", "Trans Fat Ban only", "Menu Labeling Law only", "Trans Fat Ban + Menu Labeling Law". The reference categories is “No Policy”. The coefficient is reported in exponential form, which also represents the relative risk ratio. From the result of Multinomial Logit Model, it is clear to see that the implementation of menu labeling law is influenced by the previous prevalence of dietary-related disease. This result also confirms that city with higher prevalence of chronic disease have higher probability to adopt menu labeling law.

The propensity score is constructed from the estimates of multinomial logit model. Propensity score of each unit is assigned by the predicted probability to select the treatment policy.

Table 4 reports the average treatment effect (ATE) and average treatment effect on the treated (ATET) by inverse probability weighted estimation. The dependent variables are the prevalence of hypertension and the prevalence of coronary heart disease. Given the propensity score from the multinomial logit model, the treatment effect is estimated by GLM model adjusted by

Table 3: Multinomial Logit Model for Propensity Score

	Trans Fab Ban	Menu Labeling Law	Trans Fat Ban +Menu Labeling Law
Capita Income	1.002*	1.000*	1.002***
	(2.52)	(2.15)	(3.76)
Population	1.000*	1.000	1.000**
	(2.46)	(1.72)	(3.05)
Quarterly Unemployment Rate	2.002	2.338***	11.52***
	(1.52)	(3.74)	(3.61)
Hypertension t-1	3.35863e+18*	0.0109	0.0117
	(2.11)	(-0.44)	(-0.20)
Hypertension t-2	0.000000157	0.362	6.37787e+20*
	(-0.87)	(-0.16)	(2.52)
Hypertension t-3	8.12298e+29**	0.00134	1.52294e+17
	(2.73)	(-0.70)	(1.95)
Coronary Heart Disease t-1	0.0000193	9.31e-17	1.00e-48*
	(-0.52)	(-1.34)	(-2.41)
Coronary Heart Disease t-2	0.000276	0.000257	3.27e-63***
	(-0.47)	(-0.86)	(-3.75)
Coronary Heart Disease t-3	4.20e-36*	0.0144	8.10e-55***
	(-2.49)	(-0.33)	(-3.32)
Obesity t-1	1.47e-12	2.50e-19	4.21786e+15
	(-0.40)	(-1.64)	(0.71)
Obesity t-2	1.63404e+41	4.05e-14	7.00e-29
	(1.40)	(-1.25)	(-1.24)
Obesity t-3	3.41040e+14	3.14056e+36**	1.84686e+31
	(1.14)	(2.71)	(1.47)
Observations	537		

1Data: NIS 2006-2011ï¿œ

2.Base category:No Policy

3.Year Quarter fixed effect are not reported

4.Coefficients is in the form of Relative Risk Ratio. t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the inverse probability weighted estimator. This model controlled for city population, capita per person, and year-quarterly fixed effect and city fixed effect. The reference category of the multi-valued treatment is "No Policy". In the ATE model, trans fat ban increases the prevalence of hypertension by 2 percentage point and menu labeling law decreases the prevalence of hypertension by 4 percentage point. The joint effect of two policies on the hypertension are not significantly different. The average treatment effect of trans fat ban has 1 percentage point reduction on the prevalence of CHD and menu labeling law has 2.3 percentage point reduction. The joint effect of the multiple overlapping policy decreases the prevalence of coronary heart disease by 1.38 percentage point. As for the average treatment effect on the treated, the estimation result is very similar to the ATE model. Trans fat ban increases hypertension by 2.17 percentage point. the effect of menu labeling law on the CHD seems to be greater than the effect of trans fat ban. The average treatment effect on the treated of multiple overlapping policies slightly decreases the prevalence of coronary heart disease by 1.5 percentage point.

Table 4: Inverse Probability Weighted Treatment Effect of trans fat ban and menu labeling law on prevalence of hypertension and CHD

	(1) ATE		(2) ATET	
	Hypertension	CHD	Hypertension	CHD
Trans Fat Ban	0.0203*	-0.0106*	0.0217**	-0.0109*
	(2.44)	(-2.57)	(3.04)	(-2.23)
Menu Labeling Law	-0.0485*	-0.0232*	-0.0769***	-0.0288**
	(-2.06)	(-2.10)	(-4.76)	(-2.67)
Trans Fat Ban +	-0.00354	-0.0138*	-0.00406	-0.0159**
Menu Labeling Law	(-0.24)	(-2.10)	(-0.37)	(-2.78)
N	509	509	509	509

1. t statistics in parentheses * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

2. ATE represents Average Treatment Effect; ATET represents Average Treatment Effect on the Treated

3.The reference group is "No Policy"

PART 2 Treatment effect from individual data

Among the cities with trans fat bans, this part focuses on the effect of trans fat ban in Baltimore on the individual health outcome. Baltimore is not the first U.S. city to eliminate trans fat in the restaurants, but there are several advantages to choose Baltimore as the targeted city. Most cities with trans fat ban are also associated with the menu labeling law, for example, New York City, Boston, Philadelphia. Menu labeling law requires restaurants to declare calorie counts on menus. Both trans fat ban and menu labeling law aim to improve people's dietary intake. It is difficult to credibly isolate the effect of trans fat ban from menu labeling law if two policies exist at the same time. Among the cities with trans fat ban, Baltimore is the only big city where there is no menu labeling law enforced. From September 2009, the Baltimore City Health Department started to prohibit food facility to serve food with more than 0.5 grams trans fat per serving. This paper applies difference-in-differences method to compare the effect of trans fat ban on the incidence of hypertension between treatment group (Baltimore) and seven other control group cities.

6 Data for Individual health outcome

In order to capture the change in health outcomes after the trans fat ban, I use the inpatient data from Healthcare Cost and Utilization Project (HCUP) of Nationwide Inpatient Sample (NIS) from 2004 to 2012. NIS contains more than seven million hospital stays from about 1,000 hospitals, which is sampled to a 20-percent stratified sample of U.S. community hospitals per year. Each inpatient stay record in NIS includes ICD-9-CM diagnostic and procedure information of the particular patient, which allows the researcher to identify the prevalence of certain diseases over years. The data includes not only the demographic characteristics of a patient but also the associated hospital geographic information with the hospital identifiers. Table 5 shows the summary statistics of NIS data in this paper.

The inpatient data analyzed in this paper include Baltimore, Charlotte, Chicago, Jacksonville, Miami, Milwaukee, Minneapolis, and Orlando. Treatment group in this paper is Baltimore and all the other cities serve as control groups of trans fat ban. This paper excludes patients aged less than 18 years because hypertension rarely occurs in children and adolescent. The hypertension variable is generated from the hospital diagnoses code of a patient. Applying inpatient data has the advantage to avoid the measurement error of the self-reported hypertension from health survey data. Since NIS only contains the inpatients data, this paper focuses on identifying the effect of trans fat ban on the hospitalized patients.

7 Model specification for individual data

The principal hypothesis in this paper is to check if the implementation of trans fat ban explains the changes in the number of hypertension cases in Baltimore over time. The trans fat ban in Baltimore is a natural experiment to examine the effect of trans fat intake on the prevalence of hypertension. This paper uses difference-in-differences method to measure the policy effect from treatment group and control group. The treatment group in this paper is the residents in Baltimore and the control groups are residents in Chicago . We use both linear probability model and Logit model to estimate the difference-in-differences specification. The primary estimating equation is:

$$H_{ict} = \alpha_1 + \alpha_2 Treat_j + \alpha_3 Period_t + \alpha_4 (Treat_j * Period_t) + \beta_1' X_{ijt}$$

$$+Hospital_h + YearQuarter_t + City + v_{ijt}$$

where H_{ict} is a binary health outcome of hypertension of patient i in a city j for a given year quarter t. $Treat$ is a dummy indicating if individual i belongs to the treatment group. $Period$ is a dummy for the existence of trans fat policy. α_4 is the coefficient of the interaction term as well as the estimates of "treatment effect ". X is a vector of individual-level covariates (other determinants of Hypertension). $Hospital$ is hospital fixed effect and $YearQuarter$ is year quarter fixed effect. v_{ijt} is a stochastic error term.

The dependent variable is hypertension status of a patient. The status of hypertension is constructed from a patient's ICD9 code. Each patient in HCUP NIS can have up to 15 different diagnoses, including principal diagnoses and secondary diagnoses. The binary dependent variable, H_{ict}, equals to one when any of the diagnoses of a patient has been categorized as hypertension.

The vectors covariates X include patient's gender, type of insurance, median household income for patient's zip code, status of obesity. The model also includes year-quarterly fixed effect to control the seasonality and trend over time. Hospital fixed effect in this model controls the heterogeneous characteristics for different hospitals. The model also controls total discharges per hospital year-quarterly to take into account the proportional growth of hypertension rate with the total discharges growth.

Table 5: Summary Statistics for Individual-level data

	Baltimore		Control groups	
	Before	After	Before	After
Hypertension	0.3563	0.3100	0.2817	0.2892
Age	49.6179	45.9513	44.9925	44.4616
Female	0.5764	0.5511	0.5697	0.5640
Obesity	0.1301	0.1288	0.0543	0.0792
Insurance				
Medicare	0.3707	0.3036	0.3013	0.3025
Medicaid	0.1945	0.2523	0.2895	0.3179
Private	0.3496	0.3509	0.3235	0.2643
Self Pay	0.0637	0.0585	0.0494	0.1003
No charge	0.0012	0.0029	0.0062	0.0107
Other	0.0203	0.0318	0.0301	0.0042
Income				
1st to 25th	0.2968	0.2469	0.3299	0.3452
26th to 50th	0.2068	0.2385	0.2631	0.2926
51st to 75th	0.2562	0.2306	0.2379	0.2196
76th to 100th	0.2402	0.2840	0.1691	0.1426
Observation	433,491	148,395	2,406,535	850,501

*source: HCUP NIS 2004-2011

*List of control group cities: Baltimore,Charlotte,
Chicago, Jacksonville, Miami, Milwaukee, Minneapolis, and Orlando.

7.1 Policy endogeneity

One potential identification problem for the effect of trans fat ban comes from the policy endogeneity. The unbiased estimation result is based on the assumption of exogeneity between the regressor and error term. If the policy decision of trans fat ban is responsive to the prior bad health outcome of the residents, the estimates of policy interaction term is biased. This paper uses the following two strategies to address the possible reverse causation problem.

The policy endogeneity problem can be avoided by choosing hypertension as the health outcome variable. The existence of high CHD events before trans fat ban might initiate the policy decision of trans fat ban. The local health department might pass trans fat ban in response to the prior high prevalence of CHD events. Since hypertension is just an indirect adverse effect of trans fat, the prevalence of hypertension and trans fat ban should not be highly endogenous.

Another way to overcome the endogeneity issue is to apply hospital inpatient data to analyze the trans fat ban rather than outpatient data. If the policy implementation of trans fat ban is to reduce the hypertension and CHD events, then the higher prevalence of hypertension may be the target of the trans fat ban and generate the potential endogeneity problem. However, the use of Nationwide Inpatient Sample can address part of the endogeneity problem. Hypertension is usually the secondary diagnose or comorbidity disease of a patient, which means principal diagnose of a patient to be hospitalized is mostly other diseases. Since hypertension is only a secondary diagnoses, the hypertension status of hospitalized patients should not be the goal of trans fat policy.

In order to account for the potential endogeneity problem, the sample used for DiD estimation excludes the patients with Coronary Heart Diseases. The purpose of this strategy is to avoid the CHD patients which may make the Baltimore government to decide to apply the trans fat policy. The target group of my analysis is the patients without Coronary heart diseases. We restrict the sample to the patients without the diagnose of any related coronary heart diseases.

7.2 Choice of control group:

The purpose of Difference-in-Difference method is to investigate the effect of policy intervention by comparing the changes in outcomes within treatment group and control group after the policy intervention. One important assumption of Difference-in-Differences method is the parallel trends before policy intervention. A good pair of treatment and control group should follow the similar pattern of the trend of interested outcome variable. As a result, the choice and construction of control groups in Difference-in-Differences method determines the accuracy of estimation result.

In order to select the most suitable control groups to the treatment city, Baltimore, I apply several different strategies to construct the control groups in this paper. To find similar population size of Baltimore, I take the population ranking of U.S cities as my first reference, where Baltimore ranked 26th city. The first filter is to exclude the cities with trans fat ban and menu labeling law. The next procedure is to check the data availability in NIS. Due to the restriction of data confidentiality, some states restricted the information of hospital location, and it restricts the researcher to identify the geographical information of the discharge inpatient. The inpatient data in Texas, Georgia, Michigan, Ohio, and South Carolina are excluded because of the restricted data mentioned before. The third filter is the balance of the panel data, the duration in this paper is from 2004 to 2011, and not all states participate NIS every year. In order to keep the balance of the panel, some cities are not included for missing data with certain period of time. Following by the filter above, the control groups used in this paper are listed as followed: Charlotte, Chicago, Jacksonville, Miami, Minneapolis, Milwaukee, and Orlando, in total 7 cities.

7.3 Identify the confounding effect: recession

One difficulty of identifying of the effect of trans fat policy is the timing of trans fat policy overlapped with recession. Trans fat ban in Baltimore is employed in 2009, and the recession in the U.S started in 2008. Researchers (Ruhm 2000) finds the procyclical relationship between recession and the reduction of state-level mortality rate. The impact of the recession on people's health may go through the panel by changing the frequency of dining in restaurants or changing people's other healthy behaviors.

One way to address the confounding effect of the recession is to include the county year-quarterly level of unemployment data to identify if part of the changes in hypertension rate comes from recession. The unemployment data for the city is gathered from the U.S. Bureau of Labor Statistics by city and year-quarterly. Including the unemployment data can be helpful to identify the influence of the recession on people's health condition.

8 Estimation result

8.1 The effect of Baltimore trans fat ban

Table 6 reports the estimation result of Baltimore trans fat ban. The coefficient of "Post*Treated" term provides the estimated effect of Baltimore trans fat ban on the change in percentage point of prevalence of hypertension relative to the control group cities. The difference-in-differences model is estimated by linear probability model. The first model excludes hospital fixed effect and second model include hospital fixed effect. The inpatient samples are respectively divided into two groups (1)adult: ages between 18 and 65, (2)elderly: ages older than 65. For the model without controlling hospital fixed effect, the estimate of trans fat ban is statistically significant for the elderly group. For the adult group, the effect of the trans fat ban on the prevalence of hypertension are not statically significant in linear probability model. For the elderly, the trans fat ban decreases the prevalence of hypertension by 4.65 percentage point in linear probability model. While in the

Table 6: Regression result of Baltimore trans fat ban

	Without Hospital Fixed Effect 18<Age<65	Age>=65	With Hospital Fixed Effect 18<Age<65	Age>=65
Post*Treated	-0.0151	-0.0465**	0.000592	-0.00606
	(-1.92)	(-2.58)	(0.15)	(-0.35)
Treated	0.0294***	0.0380	0.282***	-0.857**
	(3.84e+17)	(1.75)	(3.68e+18)	(-2.81)
Post	0.0222	0.0127	0.0331***	-0.00543
	(1.62)	(1.27)	(4.32e+17)	(-0.50)
Total discharge	-0.000000218	0.000000720	0.00000235***	0.00000844**
	(-0.91)	(1.46)	(3.07e+13)	(2.81)
Age	-0.00203**	0.0197***	-0.00208**	0.0198***
	(-2.81)	(2.57e+17)	(-2.81)	(2.58e+17)
Age square	0.000155***	-0.000125**	0.000155***	-0.000125**
	(2.03e+15)	(-2.81)	(2.03e+15)	(-2.81)
Unemployment rate	-0.00204	-0.00845	-0.00359*	-0.00912**
	(-0.92)	(-1.70)	(-2.58)	(-2.81)
Female	-0.0154**	0.0962***	-0.0137	0.0950***
	(-2.58)	(1.26e+18)	(-1.92)	(1.24e+18)
Diabete	0.207***	0.0812***	0.205***	0.0795***
	(2.70e+18)	(1.06e+18)	(2.68e+18)	(1.04e+18)
Constant	-0.181**	-0.00258	-0.441**	0.149***
	(-2.81)	(-0.08)	(-2.81)	(1.95e+18)
Observations	2505532	693975	2505532	693975

t statistics in parentheses

1. t statistics in parentheses with wild bootstrap standard err|s clustered at the city level

2.Source: HCUP NIS 2004-2011

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

hospital fixed effect model, the effect of the trans fat ban increases slightly 0.07 percentage point for both adult groups and elderly groups. While both of the coefficients in the hospital fixed effect model are not statistically significant, the result of the trans fat ban seems have no effect on the prevalence of hypertension.

One point to notice in Table 6 is the coefficient of unemployment rate. The timing of the recession started in 2008, and the unemployment rate starts to reflect the recession in 2009. It is necessary to control the unemployment rate in our model. It seems the recession has an impact on hypertension only for the hospital fixed effect model. The estimates of unemployment show the recession decreases the prevalence of hypertension for the adult group by 0.35 percentage point.

8.2 Inference with few clusters

With few cluster groups in the Difference-in-Differences model, the statistical inference requires extra attention for the possible biased variances matrix caused by a small size of clustered group. The concern of proper inference with few clusters in DiD specification is well-discussed in the paper Cameron et.al (2008) and Cameron et.al (2014). When the cluster number is small, the asymptotic corrections of cluster-robust-variance-estimator (CRVE) does not work well in clustered corrections. Furthermore, the Wald statistics leads to over-reject because the fitted residual used to form the predicted coefficient is also biased. There does not exist a clear threshold for what should be considered as "few". According to Cameron et.al (2014), cluster size less than 20 or less than 50 could be the case of few cluster depending on different situations. The total number of clustered groups in this model is eight (treatment group and control group are total eight cities), which definitely falls within the scope of "few clusters". Cameron et.al (2014). mentioned that few clusters in DiD still generates unbiased estimates of our interests as long as there are enough observations per clusters. In my paper, each cites include at least 200,000 observations cross year, so there is no worry for the biased estimates. However the inference for my DID model needs to be recalculated because of few clusters issue. To address the problem of few clusters in my model, I adopt wild cluster bootstrap resampling method mentioned in Caremon (2008) and estimated my model by the wildbootstrap STATA command written by Judson Caskey.

8.3 Discussion for the elderly group

From the above estimation result, in general trans fat ban has a greater effect on elderly for both models. Figure 2 shows the prevalence of hypertension in different age groups. The elderly is the highest risky group of hypertension so the policy might protect and benefit the elderly more than other groups. However, we should continue to explore the reasons behind the policy effect. There might be some other unobserved characteristics for the elderly with hypertension. High hospital utilization and the participation of Medicare for the elderly should be also considered in the model in the future.

9 Robustness Check

9.1 Count response as the outcome variable

In this section, the outcome variables is the count of hospital discharges of diet-related chronic diseases. One concern for using the National Inpatient Sample as the estimation data is that NIS only include hospitalized inpatients, which are a highly selected sample of the population. Using the proportion of a disease within the hospitalized discharges as the outcome variable might overestimate the treatment effect. To address this issue, I use the count data of hospital discharge as the outcome variable to re-examine the policy effect of trans fat ban and menu labeling law. Compared to the outpatient data, inpatient discharge data of coronary heart disease is a more representative sample of the whole population. Inpatient discharge data is also more suitable than mortality rate data because trans fat ban and menu labeling law might take a longer time to have actually effect on mortality rate. Count of hospital discharge would be a better measurement for the policy effect, because most patients with coronary heart disease have severe medical conditions which require admission to a hospital.

The count response model is estimated by Poisson regression model for the treatment effect.

$$Y_{ct} = exp(\alpha_1 + \alpha_2 Treat_{ct} + +\beta_1' X_{ct} + YearQuarter_t + City_c) + v_{ct}$$

where Y_{ct} represents the total number of diet-related diseases discharges (hypertension, coronary heart disease, cardiovascular disease) from a city c in year quarter t. Treatment is $Treat$ is a multinomial categorical indicator for four types of treatment combinations . X is a vector of time-variant city-level characteristics covariates. $City_c$ is City fixed effect and $YearQuarter$ is year quarter fixed effect. v_{ijt} is a random error term. I control the number of total discharge of a city in a given year quarter as the exposure variable of Poisson model. The function of exposure variable is to control the volume of hospital discharge in different cities. Unlike the previous aggregate model, the sample unit in the count model contains metropolitan statistic area only. The difference is that the unit with statewide menu labeling law would represent as several city units in the data. The purpose for this design is to avoid the unbalanced count response for the dependent variable.

Table 7 shows the estimation result for outcome variable as count variable estimated by the Poisson model. The coefficient is reported as the incident rate ratio. I divide the sample into adult group and elderly group. The first row of table 7 represents the effect of trans fat ban on the count of hypertension , CHD , CVD are negative and statistically significant. The rate ratio of hypertension in the city with trans fat ban would be expected to decrease by a factor of 0.91, the rate ratio of CHD decrease by a factor of 0.746 and the rate ratio of CVD decreased by a factor of 0.822 respectively. Similar pattern appeared in the elderly groups shows that trans fat ban decrease the rate ratio of hypertension by a factor of 0.93 and the rate ratio of CHD by a factor of 0.81 and decrease the risk ratio of CVD by a factor 0.891. For the effect of menu labeling law, the implementation of menu labeling law does not have significant effect on the count of hypertension population in the adult group, but menu labeling law decrease the rate ratio of hypertension among the elderly by a factor of 0.968. The estimation result of menu labeling law shows that the implemetation of menu labeling law increase 1.137 times rate ratio of CHD and CVD before the menu labeling law. It seems that the effect of menu labeling law on the prevalence of CHD and CVD is limited. The joint effect of trans fat ban and menu labeling law also decrease the prevalence of hypertension and CHD, CVD in general. Also the decrease rate is not as great as the trans fat ban alone. The result of Poisson model is consistent with the finding with the proportion dependent variables, that the effect of trans fat ban is greater than menu labeling law on the prevalence of hypertension and CHD.

9.2 Trends with CHD hospitalization and policy unrelated disease hospitalization

In this section, I construct two graphs to represent the trends of coronary heart disease hospitalization between treatment group city and control group city. Figure 1 shows the trends in hospitalization for CHD between Baltimore and Chicago. It is clear to see that the prevalence of CHD hospitalization dramatically dropped after the implementation of trans fat ban. This de-

Table 7: Poisson Estimation for count response of health outcome

	(1) Adult			(2) Elderly		
	Hypertension	CHD	CVD	Hypertension	CHD	CVD
Trans Fat Ban	0.910***	0.746***	0.822***	0.930***	0.817***	0.891***
	(-14.18)	(-25.81)	(-22.63)	(-10.86)	(-24.18)	(-16.87)
Menu Labeling Law	1.004	1.137***	1.063***	0.968**	1.077***	1.052***
	(0.41)	(7.21)	(4.49)	(-3.13)	(5.95)	(5.11)
Trans Fat + Mene Labeling Law	0.911***	0.893***	0.889***	0.915***	0.908***	0.930***
	(-9.61)	(-6.91)	(-9.56)	(-9.31)	(-8.09)	(-7.44)
Quarterly Unemployment Rate	0.982***	0.985***	0.984***	0.996*	1.003	1.000
	(-10.07)	(-5.24)	(-6.85)	(-2.18)	(1.30)	(0.04)
Population	1.000	1.000	1.000	1.000	1.000	1.000
	(-1.11)	(0.43)	(0.64)	(0.79)	(1.47)	(0.03)
Capita Income	1.000***	1.000	1.000	1.000	1.000***	1.000
	(-7.59)	(0.19)	(-1.71)	(0.24)	(5.06)	(1.60)
Constant	0.293***	0.100***	0.178***	0.377***	0.226***	0.491***
	(-22.75)	(-26.63)	(-25.39)	(-19.04)	(-23.58)	(-13.85)
Observations	996	996	996	983	983	983

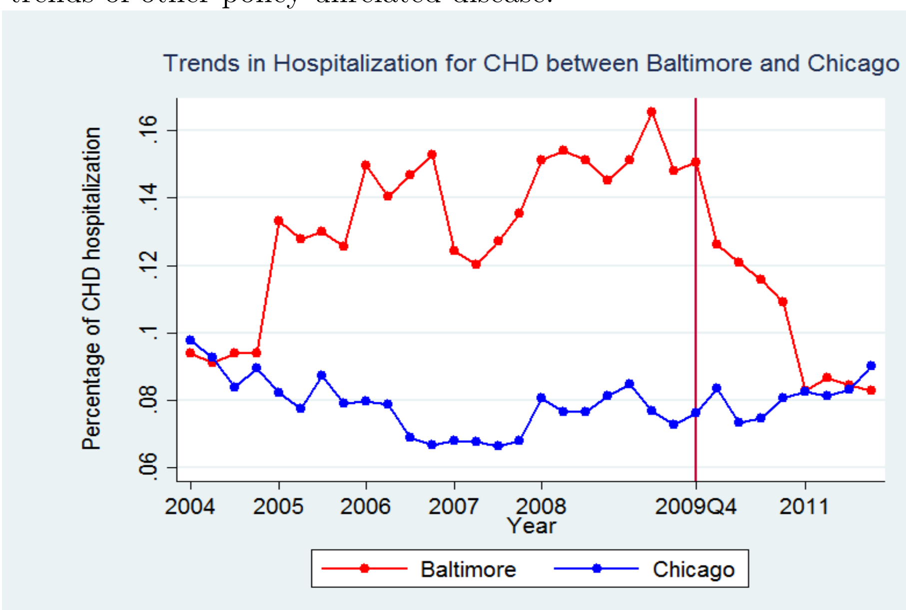
Note: 1. CHD- Coronary Heart Disease. CVD: Cardiovascular Disease

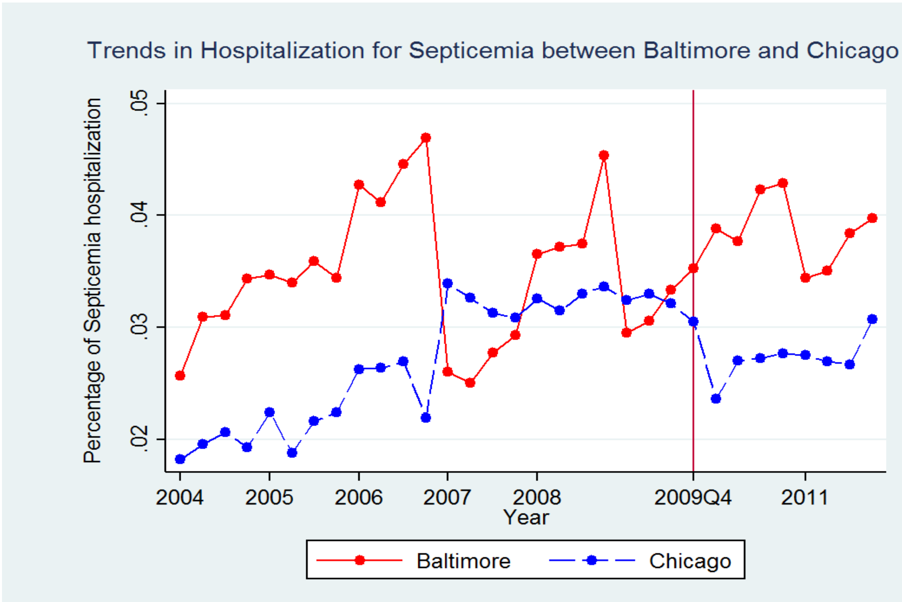
2. Coefficient form as incidence rate ratio

3. Year quarter fixed effect and city fixed effect are not included.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

creasing trend of CHD hospitalization in figure 1 also supports the previous estimation result. To make sure the trends of CHD is not related to change of admission volume overtime, I construct another figure to capture the trend of another disease that is not related to either trans fat ban nor menu labeling law. In a statistical report by HCUP with the information of most frequent principal diagnoses in U.S hospitals, the number of septicemia hospitalization has the similar ranking as the number of CHD hospitalization. Figure 2 shows the trend of Septicemia hospitalization between Baltimore and Chicago. As shown in figure 2, the trend of Septicemia does not have the same pattern as that of CHD. The random trends of septicemia shows that trans fat ban is related to the trends of CHD hospitalization but not the trends of other policy unrelated disease.





10 Final Remark and Future Work

This paper investigates the joint policy impact of trans fat ban and menu labeling law on the prevalence of hypertension and coronary heart disease. I estimate the treatment effect of these two policies by inverse probability weighting estimator. We find trans fat ban decreases the prevalence of coronary heart disease by 2 percentage point. The average treatment effect of multiple overlapping policies slightly decreases the prevalence of coronary heart disease by 1.4 percentage point. The average treatment effect on the treated of multiple overlapping policies decreases the prevalence of coronary heart disease by 1.59 percentage point. The limitation of this paper is that the validity of the estimation result relies upon a conditional independent assumption (CIA) in the potential outcome model. The conditional independent assumption assumes that the selection into the treatment is independent from the treatment outcome, given the observed characteristics, while in reality it is difficult for the researcher to observe the characteristics related to the treatment selection mechanism. Future research could develop in the following directions: (1) the future model should consider the nested relationship between Metropolitan Statistical Areas (MSA) and states. Due to the limitation of data and technical problems, I could only treat these two types of political divisions as the same level of unit. Including a multi-level setup in the nested model would help the researcher address the unbalanced problem within samples. (2) The dependent variable used in the average treatment effect model is a fraction response variable. The choice of estimation model could later extend to a nonlinear panel data model, proposed by Wooldridge (2008).

References

[1] Angell, Sonia Y., Laura K. Cobb, Christine J. Curtis, Kevin J. Konty, and Lynn D. Silver. "Change in Trans Fatty Acid Content of Fast-Food Purchases Associated With New York City's Restaurant RegulationA Pre–Post Study." Annals of internal medicine 157, no. 2 (2012): 81-86.

[2] Baltimore City Health Department Trans Fat Ban Enforcement Procedure. Online link: http://baltimorehealth.org/transfat.html

[3] Bollinger, Bryan, Phillip Leslie, and Alan Sorensen. Calorie posting in chain restaurants. No. w15648. National Bureau of Economic Research, 2010.

[4] Bradley, Steve, and Giuseppe Migali. "The joint evaluation of multiple educational policies: the case of specialist schools and Excellence in Cities policies in Britain." Education Economics 20, no. 3 (2012): 322-342.

[5] Cameron, A. Colin, and Douglas L. Miller. "A Practitioner's Guide to Cluster-Robust Inference." Forthcoming in Journal of Human Resources (2013).

[6] Cameron, A. Colin, Jonah B. Gelbach, and Douglas L. Miller. "Bootstrap-based improvements for inference with clustered errors." The Review of Economics and Statistics 90, no. 3 (2008): 414-427.

[7] Cattaneo, Matias D. "Efficient semiparametric estimation of multi-valued treatment effects under ignorability." Journal of Econometrics 155, no. 2 (2010): 138-154.

[8] Downs, Shauna M., Anne Marie Thow, and Stephen R. Leeder. "The effectiveness of policies for reducing dietary trans fat: a systematic review of the evidence." Bulletin of the World Health Organization 91, no. 4 (2013): 262-269h.

[9] Grynberg, A. "Hypertension prevention: from nutrients to (fortified) foods to dietary patterns. Focus on fatty acids." Journal of human hypertension 19 (2005): S25-S33.

[10] Hirano, Keisuke, Guido W. Imbens, and Geert Ridder. "Efficient estimation of average treatment effects using the estimated propensity score." Econometrica 71, no. 4 (2003): 1161-1189.

[11] Imbens, Guido W. "Nonparametric estimation of average treatment effects under exogeneity: A review." Review of Economics and statistics 86, no. 1 (2004): 4-29.

[12] Kiszko, Kamila M., Olivia D. Martinez, Courtney Abrams, and Brian Elbel. "The Influence of Calorie Labeling on Food Orders and Consumption: A Review of the Literature." Journal of community health (2014): 1-22.

[13] Krieger, James W., Nadine L. Chan, Brian E. Saelens, Myduc L. Ta, David Solet, and David W. Fleming. "Menu labeling regulations and calories purchased at chain restaurants." American journal of preventive medicine 44, no. 6 (2013): 595-604.

[14] Law, Malcolm R., Nicholas J. Wald, and S. G. Thompson. "By how much and how quickly does reduction in serum cholesterol concentration lower risk of ischaemic heart disease?." Bmj 308, no. 6925 (1994): 367-372.

[15] Lechner, Michael. "Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies." Review of Economics and Statistics 84, no. 2 (2002): 205-220.

[16] Lechner, Michael. Identification and estimation of causal effects of multiple treatments under the conditional independence assumption. Physica-Verlag HD, 2001.

[17] Mensink, Ronald P., and Martijn B. Katan. "Effect of dietary trans fatty acids on high-density and low-density lipoprotein cholesterol levels in healthy subjects." New England Journal of Medicine 323, no. 7 (1990): 439-445.

[18] Micha, R., and D. Mozaffarian. "Trans-fatty acidss: effects on cardiometabolic health and implications for policy." Prostaglandins, Leukotrienes and Essential Fatty Acids 79, no. 3 (2008): 147-152.

[19] Mozaffarian, D., A. Aro, and W. C. Willett. "Health effects of trans-fatty acids: experimental and observational evidence." European journal of clinical nutrition 63 (2009): S5-S21.

[20] Mozaffarian, Dariush, Martijn B. Katan, Alberto Ascherio, Meir J. Stampfer, and Walter C. Willett. "trans-fatty acidss and cardiovascular disease." New England Journal of Medicine 354, no. 15 (2006): 1601-1613.

[21] Nicklas, Theresa A., Tom Baranowski, Karen W. Cullen, and Gerald Berenson. "Eating patterns, dietary quality and obesity." Journal of the American College of Nutrition 20, no. 6 (2001): 599-608.

[22] Oh, Kyungwon, Frank B. Hu, JoAnn E. Manson, Meir J. Stampfer, and Walter C. Willett. "Dietary fat intake and risk of coronary heart disease in women: 20 years of follow-up of the nurses' health study." American Journal of Epidemiology 161, no. 7 (2005): 672-679.

[23] Restrepo, B (2014), "Calorie Labeling in Chain Restaurants and Body Weight: Evidence from New York", European University Institute Max Weber Programme Working Paper (2014)

[24] Restrepo, B and M Rieger (2014), "Trans Fat and Cardiovascular Disease Mortality: Evidence from Bans in Restaurants in New York", European University Institute Max Weber Programme Working Paper (2014)

[25] Ruhm, Christopher J. Are recessions good for your health?. No. w5570. National bureau of economic research, 1996.

[26] Vesper, Hubert W., Heather C. Kuiper, Lisa B. Mirel, Clifford L. Johnson, and James L. Pirkle. "Levels of plasma trans-fatty acids in non-Hispanic white adults in the United States in 2000 and 2009." JAMA: The Journal of the American Medical Association 307, no. 6 (2012): 562-563.

[27] Wang, Lu, JoAnn E. Manson, John P. Forman, J. Michael Gaziano, Julie E. Buring, and Howard D. Sesso. "Dietary fatty acids and the risk of hypertension in middle-aged and older women." Hypertension 56, no. 4 (2010): 598-604.

[28] Wooldridge, Jeffrey M. "Inverse probability weighted M-estimators for sample selection, attrition, and stratification." Portuguese Economic Journal 1, no. 2 (2002): 117-139.

11 Appendix

The appendix includes the analysis of New York City trans fat ban. The possibly confounding effect of menu labeling law in NYC may lead to biased estimates of trans fat ban so I decide to include the result of NYC in the appendix.

11.1 Trans Fat Ban in NYC

In 2006, New York City (NYC) department of Health and Mental Hygiene amended NYC health code to restrict the presence of trans fat in foods served in restaurants. This code is phased out by two periods. First of all, by July 1 2007, all restaurants in NYC had to remove artificial trans fat from all oils, shortening and margarines. Then, by 1 July 2008, all foods served in restaurants can only contain less than 0.5g of trans fat per serving.

Restaurants that violate trans fat ban are subject to recieve fines from $200 to $2,000.

11.2 Overlapping with menu-labeling law

In addition to the trans fat ban, NYC department of health enacts menu-labeling policy that could also possibly affect the prevalence of hypertension. Menu-labeling law mandates chain restaurants to post calories information on menus. The law is implemented in May 5, 2008. The implemented time is right between the phasing out period of trans fat policy. In order to identify the effect of menu-labeling law, we construct one variable for menu labeling law. However, if the implication of menu-labeling law and trans fat policy is highly correlated and if the enact of menu-labeling ban and trans fat ban are determined by the same omitted variable, the estimates would be problematic.

Another possible way to identify the effect purely from trans fat ban is to check another city with trans fat policy but without menu-labeling law. The most suitable cities are Baltimore and Boston. Baltimore implemented trans fat ban in Sep, 2009 and does not have menu-labeling law by far. Similar to NYC, Boston phased out trans fat in two periods: first to eliminate trans fat in the oil and shortening in September 2008, and then all food without trans fat in Mar 12, 2009. Boston started menu-labeling law in November 2010.

11.3 Model specification

NYC department of health phased out trans fat in two different time periods. The first period is to restrict the trans fat policy appear in oil, margarine and shortening in July,2007. The second period is to restrict trans fat in all kinds of food. In order to capture the two periods phasing-out policy, I construct two types of difference-in-differences models. The first model considers July 2007 as the main cut-off point, so the time dummy variable of trans fat policy equals to one after 2007 Q3.

$$H_{ict} = \alpha_1 + \alpha_2 Treat_j + \alpha_3 Period_t + \alpha_4 (Treat_j * Period_t) + \beta_1' X_{ijt} + Hospital_h + YearQuarter_t + v_{ijt}$$

where H_{ict} is a binary health outcome of hypertension of patient i in a city j for a given year quarter t. $Treat$ is a dummy indicating if individual i belongs to the treatment group. $Period$ is a dummy for the existence of trans fat policy. α_4 is the coefficient of the interaction term as well as the estimates of "treatment effect ". X is a vector of individual-level covariates (other determinants of Hypertension). $Hospital$ is hospital fixed effect and $YearQuarter$ is year quarter fixed effect. v_{ijt} is a stochastic error term.

The second model takes the two phasing-out periods into consideration. The time between 2007 July and 2008 July is the transition period, so this model include both "during" and "after" effect. The interaction term NYC*during is the effect of the effect on that particular period and

NYC*after is the effect of trans fat policy after 2008Q3.

$$
\begin{aligned}
H_{ict} &= \alpha_1 + \alpha_2 Treat_j + \alpha_3 After_t + \alpha_4 During \\
&+ \alpha_5 (Treat_j * After_t) + \alpha_6 (Treat_j * During) \\
&+ \beta_1' X_{ijt} + Hospital_h + YearQuarter_t + v_{ijt}
\end{aligned}
$$

The dependent variable is hypertension status of a patient, which is constructed from the diagnose ICD9 code. The diagnose indicator in NIS can be recorded up to 15 different ICD9 codes. We construct a binary variable to distinct the hypertension status of a patient. The binary dependent variable equals to one if any of those 15 diagnose indicators has been categorized as hypertension.

The vectors covariates X include patient's gender, type of insurance, median household income for patient's zip code, status of obesity. The model also includes year-quarterly fixed effect to control the seasonality and trend over time. Hospital fixed effect in this model controls the heterogeneous characteristics for different hospitals. The model also controls total discharges per hospital year-quarterly to take into account for the proportional growth of hypertension rate with the total discharge growth .

11.4 Estimation result of New York City

For the first model, the estimation result in table 6 shows the decrease in the prevalence of hypertension by 0.6 percentage point for the group of all ages after NYC trans fat policy. If we look into the decomposition of age group, the change in hypertension is not significantly different. For the second model, if we construct the time period as during and after the trans fat ban, the result indicates a statistically significantly decrease in hypertension rate among elderly by 2.67 percentage point. However, the result remains insignificant for the non-elderly in hypertension rate.

The estimate of the model is sensitive with the variable of menu-labeling law. The timing of implementing trans fat policy is too close to menu-labeling law, which creates multi-colinearity problem if including both policy variables. The estimates of trans fat policy might be more meaningful in the model of Baltimore.

Moreover, the estimates of other covariates provide the consistent information that obesity increases with higher probability of hypertension and decreases with the growth of income. By including the unemployment rate in the model to check the effect of recession on the hypertension, we find that the recession has no effect on the hypertension in this model.

Table 8: Regression result of NYC trans fat ban:Model 1

	(1)Age>18		(2)18<AGE<65		(3)AGE>65	
	Linear	Logit	Linear	Logit	Linear	Logit
main interaction	-0.00675**	0.969*	-0.00554*	0.977	-0.00600	0.975
	(-2.82)	(-2.40)	(-2.09)	(-1.32)	(-1.29)	(-1.35)
treat	0.0612***	1.342***	0.0142*	1.135**	0.177***	2.093***
	(10.55)	(9.22)	(2.37)	(3.26)	(12.00)	(12.05)
period	0.0255***	1.141***	0.0294***	1.180***	0.0166	1.071
	(5.25)	(4.99)	(5.52)	(4.70)	(1.74)	(1.74)
Carolie	-0.00533*	0.959**	0.00271	1.017	-0.0295***	0.887***
	(-1.97)	(-2.82)	(0.92)	(0.85)	(-5.48)	(-5.42)
Total discharge	-0.00000745***	1.000***	-0.00000429***	1.000***	-0.0000117***	1.000***
	(-9.67)	(-9.69)	(-5.02)	(-5.17)	(-7.85)	(-7.90)
Unemployment rate	0.00333*	1.020*	-0.0000866	1.004	0.00921**	1.038**
	(2.18)	(2.38)	(-0.05)	(0.31)	(3.21)	(3.15)
Age	0.0252***	1.250***	0.00356***	1.298***	0.0255***	1.111***
	(269.27)	(315.63)	(19.22)	(134.58)	(19.63)	(19.65)
Age square	-0.000136***	0.999***	0.000118***	0.998***	-0.000160***	0.999***
	(-161.30)	(-250.25)	(54.50)	(-89.19)	(-19.55)	(-19.57)
Female	0.0133***	1.070***	-0.0205***	0.887***	0.0741***	1.356***
	(20.26)	(19.39)	(-27.67)	(-25.39)	(59.55)	(59.31)
Obesity	0.191***	2.635***	0.218***	3.062***	0.0969***	1.522***
	(117.88)	(112.73)	(130.87)	(114.80)	(25.84)	(25.82)
Constant	-0.569***	0.000236***	-0.110***	0.000129***	-0.575***	0.0118***
	(-40.90)	(-107.78)	(-6.98)	(-80.14)	(-9.98)	(-18.65)
Observations	1874898	1874898	1252667	1252667	663057	663055

t statistics in parentheses

1.t statistics in parentheses

2.Source: HCUP NIS 2004-2010

3.Odds Ratio is reported in Logit model

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

Table 9: Regression result of NYC trans fat ban

	(1)Age>18		(2)18<AGE<65		(3)AGE>65	
	Linear	Logit	Linear	Logit	Linear	Logit
main						
nyduring	-0.00839***	0.958***	-0.00632**	0.968*	-0.0107*	0.956**
	(-3.91)	(-3.62)	(-2.67)	(-2.04)	(-2.57)	(-2.61)
nyafter	-0.0122***	0.935***	-0.00602	0.955	-0.0267***	0.897***
	(-3.69)	(-3.65)	(-1.67)	(-1.86)	(-4.10)	(-4.06)
Carolie	-0.00267	0.977	0.00217	1.029	-0.0173**	0.931**
	(-0.82)	(-1.32)	(0.60)	(1.17)	(-2.77)	(-2.78)
treat	0.0614***	1.345***	0.0141*	1.136**	0.179***	2.113***
	(10.60)	(9.30)	(2.36)	(3.28)	(12.16)	(12.20)
during	0.0280***	1.166***	0.0180***	1.118***	0.0435***	1.194***
	(7.31)	(7.38)	(4.11)	(3.81)	(6.21)	(6.17)
after	0.0266***	1.150***	0.0299***	1.186***	0.0207*	1.089*
	(5.50)	(5.30)	(5.63)	(4.86)	(2.17)	(2.17)
Total discharge	-0.00000750***	1.000***	-0.00000427***	1.000***	-0.0000120***	1.000***
	(-9.73)	(-9.78)	(-5.00)	(-5.20)	(-8.02)	(-8.07)
Unemployment rate	0.00348*	1.021*	-0.0000763	1.004	0.00969***	1.040***
	(2.27)	(2.45)	(-0.04)	(0.32)	(3.37)	(3.31)
Age	0.0252***	1.250***	0.00356***	1.298***	0.0255***	1.111***
	(269.27)	(315.63)	(19.22)	(134.58)	(19.62)	(19.64)
Age square	-0.000136***	0.999***	0.000118***	0.998***	-0.000160***	0.999***
	(-161.31)	(-250.25)	(54.50)	(-89.19)	(-19.54)	(-19.56)
Female	0.0133***	1.070***	-0.0205***	0.887***	0.0741***	1.356***
	(20.26)	(19.40)	(-27.67)	(-25.39)	(59.56)	(59.32)
Obesity	0.191***	2.635***	0.218***	3.062***	0.0968***	1.522***
	(117.88)	(112.73)	(130.87)	(114.80)	(25.81)	(25.80)
Constant	-0.571***	0.000234***	-0.111***	0.000129***	-0.581***	0.0115***
	(-40.87)	(-107.46)	(-6.98)	(-79.92)	(-10.07)	(-18.73)
Observations	1874898	1874898	1252667	1252667	663057	663055

t statistics in parentheses

1.t statistics in parentheses

2.Source: HCUP NIS 2004-2010

3.Odds Ratio is reported in Logit model

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