Food Environment and Weight Outcomes:
A Stochastic Frontier Approach

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Abstract

Food environment includes the presence of supermarkets, restaurants, warehouse clubs and supercenters, and other food outlets. This paper evaluates weight outcomes from a food environment using a stochastic production frontier and an equation for the determinants of efficiency, where the explanatory variables of the efficiency term include food environment indicators. Using individual consumer data and food environment data from New England counties, empirical results indicate that fruit and vegetables markets and full-service restaurants are negatively associated with weight outcomes, while warehouse clubs and supercenters are positively related. Supermarkets and other grocery stores, convenience stores and limited-service eating places are not significantly linked to weight gain. Farrell's efficiency indexes are used to rank states and counties and several policy implications are suggested.

Key words: food environment, obesity, stochastic frontier
JEL Codes: I12

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Introduction

Obesity in the United States has been increasingly cited as a major health issues in recent decades. In 2010, approximately 36% of American adults and 17% of children were obese (Ogden et al., 2012). As a serious pandemic, obesity contributed to an additional cost of $ 117 billion in 2008 (Finkelstein et al., 2009). A substantial volume of previous work has focused on the obesity epidemic and the effectiveness of policy interventions to curb its incidence. In addition to factors such as individual socio-demographics (including income, age, race, number of children, gender, etc.), behavioral characteristics (e.g., physical activity, smoking, drinking, etc.) and socio-economic factors (e.g., labor market conditions, economic recessions and peer effects), the food environment is receiving increasing attention.

The food environment is defined by the National Cancer Institute (NCI) to include "food stores, restaurants, schools and worksites."[1] Similarly, McKinnon et al. (2009) categorized the food environment as the "food store environment (e.g., grocery stores, supermarkets, specialty food stores, farmers' markets, and food pantries); restaurant food environment (e.g., fast food and full-service restaurants); school food environment (e.g., cafeterias, vending machines, and snack shops in daycare settings, schools and/or colleges); and/or worksite food environment (e.g., cafeterias, vending machines, snack shops)." The USDA defines food environment factors as store/restaurant proximity, food prices, food and nutrition assistance programs, and community characteristics as they interact to influence food choices and diet quality.[2] This paper emphasizes

[1] See https://riskfactor.cancer.gov/mfe
[2] See http://www.ers.usda.gov/data-products/food-environment-atlas.aspx

the availability of food outlets of different industrial categories. Following Bonanno and Goetz (2010), food outlets are categorized in this paper by industry definitions, which include supermarkets and other grocery stores, convenience stores, fruit and vegetable markets, warehouse clubs and supercenters, full-service restaurants and limited-service eating places.

Supermarkets generally offer high-quality and low-cost food (Powell et al, 2007). Morland et al. (2006) report that the presence of supermarkets is associated with a lower prevalence of obesity and overweight. Chen et al. (2010) find that the effect of improvements in chain grocer access on BMI varies depending on community characteristics. More specifically, increasing access to chain grocers in low-income communities decreased the average BMI for all respondents by approximately 0.3. Regarding supermarket access, a USDA report (2009), indicates that approximately 2 million U.S. households live more than a mile from a supermarket. Living in the “food deserts” have been found associated with lower quality diets and increased risk of obesity.

Convenience stores are generally regarded as posing an increased risk of being obesity since they generally offer less variety, higher prices and lower quality produce than supermarkets (Zenk and Powell, 2008). For example, Morland et al (2006) find that convenience stores are positively associated with a higher prevalence of obesity and overweight.

Fruit and vegetable markets as well as local agriculture are also documented as factors that impact weight outcomes. Lin and Morrison (2003) provide evidence that consuming fruit and vegetables decreases body mass index (BMI) by examining the diet of school-aged children and adults. Berning (2012) shows that access to local agriculture (farmers’ market and community supported agriculture) is negatively associated with weight gain.

Warehouse clubs and supercenters are also linked with the prevalence of obesity. Courtemanche and Carden (2010) find that the density of Wal-Mart Supercenters is positively correlated with obesity rates, using data from the BRFSS matched with Wal-Mart Supercenter entry dates and locations.

Full-service restaurants are generally regarded as serving healthier foods. However, the role of full-service restaurants is still controversial. Some researchers find evidence that full-service restaurants are associated with lower weight status. For example, Mehta and Chang (2008) analyze the relationship between a restaurant environment and weight status across counties in the United States, finding a negative association between availability of full-service restaurants and the prevalence of overweight and obesity. However, some researchers for example Powell and Nguyen (2013), find that full-service restaurant consumption is associated with a net increase in daily total energy intake of 160 kcal for children and 267 kcal for adolescents. They conclude that full-service restaurant consumption is associated with higher net total energy intake and poorer diet quality.

Other studies find that access to low-quality food away from home, particularly from fast-food restaurants, has a positive effect on obesity rates. For example, Chou et al. (2004), combining state-level data with individual demographic and weight data from the Behavioral Risk Factor Surveillance Survey (BRFSS), present evidence that the per capita number of fast-food restaurants positively affects rates of obesity. Currie et al. (2010) find that an increase in fast-food restaurants lead to an increase in obesity and weight gains among ninth-graders and pregnant mothers. Dunn (2010) employs an identification strategy based on county-level variation in the number of fast-food restaurants and shows that availability of them is correlated with the increased BMI among females, and non-whites in medium density counties. However, Anderson and Matsa (2009) find no causal link between food consumption at restaurants (both fast-food and full-service restaurants) and obesity using food-intake micro data and correcting for endogenous location of establishments.

Previous work has focused on the impact of different aspects (e.g., outlets) of the food environment on weight outcomes. However, a comprehensive study of the relationship between the food environment and weight gain is lacking. The omission of an analysis that comprehensively includes various components of the food environment can lead to not only biased results but also disallow a direct comparison of the importance of different determinants of weight outcomes. Comprehensively measuring the impact of the food environment on weight outcomes requires an integrated framework that accounts not only for food environment factors but also for consumer characteristics.

This paper applies a stochastic frontier approach (SFA) to extend the health production function development by Grossman (1972), using bodyweight as output given consumers' demographics and behavioral characteristics and treating food environmental factors as determinants of deviations from the frontier. The food environment can affect weight outcomes in different ways. First, food environments can affect food-access costs. In general, people living in poor food environments need to pay more (e.g., time, transportation cost) to obtain food. The diversion of resources into unproductive uses leads to inefficiency (Collier, 1999). Second, different food environments imply different availability of types of food (e.g., healthy and unhealthy) in consumers' choice set. In poor food environments, healthy foods are fewer so that consumers' choices are bounded and they cannot allocate limited resources efficiently. Third, in the long run, the food environment might reshape people's eating style and habits. For example, there is evidence from medical research that the nutrients in fast food are inherently addictive (Colantuoni et al., 2002; Grigson, 2002; Del Parigi et al., 2003).

Using New England data at the county level, results from stochastic frontier model indicate that the presence of supermarkets and other grocery stores, fruit and vegetables markets and full-service restaurants are negatively associated with weight outcomes, while warehouse clubs and supercenters are positively associated. In addition, this paper evaluates the health "efficiency" for different aspects of the environment, ranks them by state and counties, and suggests policy implications.

Empirical Model

The empirical framework relies on a stochastic production function and an equation for the determinants of efficiency, where the explanatory variables of the efficiency term include food environment indicators. Adapting the health production function proposed by Grossman (1972), a stochastic frontier health production function with technology inefficiency is given as:

$$H = H(F, E, D, Z)\, exp(v)\, exp(-u), \tag{1}$$

where H is the health status, F is food intake, E is physical activities, D is demographic characteristics such as age, education, race, income and gender, and Z stands for the fixed effects of location (county) and time (year). v is the unobservable individual characteristics which make the production frontier stochastic. u is an efficiency term for health production. The production function $H(F, E, D, Z)$ is deterministic output given inputs combinations. Efficiency is defined in terms of the ratio of the observed production to the corresponding stochastic frontier value (Verburg et al., 2000).

$H(F, E, D, Z)$ is assumed to take a Cobb-Douglas form. Taking the logarithm of both sides, the empirical model is given by:

$$y_{ik} = x_i'\beta + v_{ik} - u_{ik} \tag{2}$$

where subscripts i, k denote individual consumer i in food environment k. y_{ik} is the log measure of health outcome; x_i denotes the log of consumer characteristics; v_{ik} is a random symmetric disturbance accounting for noise assumed to be independently identically distributed with a mean of zero and variance σ_v^2; u_{ik} is an asymmetric error term that accounts for systematic deviations from the frontier due to food environment factors where the individual i resides.

Given that weight outcomes are associated with negative health outcomes such as type II diabetes, hypertension, cardiovascular disease and disability, the empirical model in (2) can be expressed as:

$$logBMI_{ik} = x_i'\beta + v_{ik} + u_{ik} \tag{3}$$

This paper follows Battese and Coelli (1993) who estimated a stochastic frontier model incorporating a technical inefficiency term which is a linear function of several factors. Specifically, the following function is estimated along with the production function in (3):

$$u_{ik} = z_{ik}'\delta + \omega_{ik}, \tag{4}$$

where z_{ik}' denotes a set of indicators for food environment, δ is a corresponding vector of parameters, and ω_{ik} is a random error which distributes independently of v_{ik} and follows a truncated normal distribution with a zero mean and variance σ_u^2 with truncation point at $-z_{ik}'\delta$, i.e., $w_{ik} \geq -z_{ik}'\delta$. In this study, factors of food environment such as the density of food stores and restaurants are included in explanatory variable z_{ik} to test whether the food environment causes efficiency for BMI production.

Data and Estimation

Table 1 presents the definitions and descriptive statistics of the variables in the sample. The main data source used to estimate the model is the BRFSS annual survey data from the

Centers for Disease Control and Prevention during 2001-2010. This survey consists of a self-reported annual survey of more than 350,000 consumers throughout the United States, which provides data on body mass index (BMI) and consumer characteristics and on health care, risky behaviors, disease prevalence and preventive health practices. New England states provide a good case study since the obesity rate in this area is relatively lower than in other regions but experiencing a significant increase during these ten years. To obtain indicators of the food environment, the individual observations are grouped by county and matched with data from the County Business Patterns during 2001-2010 to include the number of establishments in the following industries: supermarkets and other grocery stores (NAICS 44511), convenience stores (NAICS 44512), warehouse clubs and supercenters (NAICS 45291), fruit and vegetables stores (NAICS 44523), full-service restaurants (NAICS 72210), and limited-service eating places (NAICS 72211)[3].

[3] According to the definition from U.S. Bureau of Census (USBC), NAICS 44511 comprises establishments generally known as supermarket and grocery stores primarily engaged in retailing a general line of food, such as canned and frozen foods; fresh fruits and vegetables; and fresh and prepared meats, fish and poultry. NAICS 44512 comprises establishments known as convenience stores or food marts (except those with fuel pumps) primarily engaged in retailing a limited line of goods that generally included milk, bread, soda and snacks. The establishments in industry NAICS 44523 are primarily engaged in retailing fruits and vegetables via electronic home shopping, mail-order, or direct sales and growing and selling vegetables and or/ fruits at roadside stands. NAICS 45291 includes warehouse clubs and supercenters, primarily engaged in retailing a general line of groceries in combination with general lines of new merchandise such as apparel, furniture, and appliances. The establishments in industry NAICS 72211 are primarily engaged in providing food services to patrons who order and are served while seated and pay after eating. The industry NAICS 72221 comprises establishments primarily engaged in providing food services where patrons generally order or select items and pay before eating; most of these establishments do not

Following Dunn (2010) and Courtemanche and Carden (2010), we use numbers of food suppliers per 1000 persons to approximate availability. Normalizing by population implicitly assumes that all food outlets and population are uniformly distributed across a county (Berning, 2012). The population data used in this paper is from USCB Population Estimates Program.

Since the respondents in the BRFSS survey data are not the same over time, the data structure is not a panel. Thus, the observations are pooled. The availability of food outlets is potentially endogenous, arising from two sources. One is the correlation between the availability of food outlets and unobservable individual characteristics. For instance, an individual's eating habits, health consciousness and demand for food might affect his/her BMI level as well as the presence of food outlets. The other is the correlation between the density of food outlets and county characteristics. Food outlet establishments are more likely to enter counties where there is higher demand for them[4].

To account for endogeneity, this paper follows Dunn (2010) by including a set of instruments as well as a standard set of county-level controls: median county income, county population density, crime rates (violence and property crime) at county level, mean travel time to work in

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have waiter/waitress service, but some provide limited service such as cooking to order (i.e., per special request), bringing food to seated customers, or providing off-site delivery.

[4] An example from Dunn (2010) is that restaurants may be more likely to open in wealthier counties, which are also more likely to have grocery stores, clean parks and beaches, farmers' markets and low crime rates. Restaurants may concentrate in densely populated counties where individuals are more likely to walk to work or use public transportation. Alternatively, densely populated areas may inhibit the exercise opportunity to bicycle or run. Counties with large distances between residential and commercial areas will tend to attract restaurants along commuting routes, and decrease the amount of time available for preparing meals at home and exercising. Another example is from Sturm (2008) who finds that convenience stores are more close to the schools with more Hispanic and Black students.

each county[5]. Instrumental variables used in this paper include the number of high-way exits (Dunn, 2010), and the three-period lag of density of food environment components (Rashad et al., 2006). Highway exits are explicitly explained as valid instruments for fast food restaurants. Given that convenience stores are generally combined with gas stations, which are generally located near highway exits, the number of highway exits is also a good instrument for convenience stores. In addition, food outlets usually expand based on market demand. The current availability of food outlets is likely to be correlated with consumers' demand in the current period or last several periods. To address this, three-year-lagged variables for food outlet availability are used as instruments because they are unlikely to correlate with the unobserved demand shocks (Rashad et al. 2006).

Empirical Results

Table 2 reports the results from equation (3). Physical activity is potentially endogenous, so estimation results with/without physical activity are reported as models (1) and (2). The results in these two models are quite similar. We find that age, education and income has a "U-shape" relationship with BMI while number of children has an "inverse U-shape" one. Female, White and Asian have relatively lower weights compared with Black and Hispanic. Married people are found to have a larger BMI. Behaviors like smoking and drinking are negatively associated with high weight outcomes. Having a sedentary job or being retired are likely to increase weight while physical activity and exercise decrease the weight outcome.

[5] The mean time to travel to work and median income are respectively from USCB Small Area Income and Poverty Estimates, the crime rate including violence crime and property crime is from USA Counties and Uniform Crime Reporting. The number of highway exits which used as instrumental variable is collected from Wikipedia. Other information like square miles of land in each county is from the U.S. Census Bureau (USCB) Gazetteer of Counties.

In addition, the negative coefficients of fruit and vegetables markets and full-service restaurants indicate that food environment with higher availability of them are more efficient for health production. The positive coefficient for warehouse club and supercenters implies that higher availability of it tend to be more inefficient. We also find that supermarkets increase efficiency for health production and convenience stores and limited service restaurants decrease health production efficiency, although insignificantly.

Other social-economic factors also matters. Health production efficiency is higher in the wealthier counties, while a higher crime rate decreases the efficiency significantly, possible reason being that a high crime rate might prevent outdoor activity; but counties with higher population density have higher health production efficiency.

With the estimate results, Farrell's (1957) technical efficiency index can be calculated for each individual by state, county and time. We calculate an average technical efficiency index by state and year and list it in Table 3. Based on this table, Connecticut has the highest efficiency while Maine is lowest ranked. Other states following Connecticut are, in order, Massachusetts, New Hampshire, Vermont and Rhode Island. Corresponing to this table, Figure 1 shows fluctuations of efficency index for Connecticut, Maine, Massachusetts during 2001-2010[6]. The efficiency index decreases from year 2001 to year 2002, and hits the top at year 2003 and year 2009. The fluctuation of these curves to some extent has a pattern similar to the macro-economy, which is in recession in year 2001 and a great recession from December 2007 to June 2009 (NBER). This finding is consistent with some literature, e.g., Huffman and Rizov (2007), who find obesity rates varies with economy conditions.

[6] These three states are chosen as examples because CT ranks highest and ME ranks lowest while MA has most population

Table 4 lists the health production efficiency rankings by county. Due to missing data ten counties were dropped. Kennebec County rankd first, Somerset County last. Figure 4 is a map of the efficiency index during 2001-2010, which are categorized into five levels illustrated by different colors using GIS software.

Concluding Remarks

This paper estimates the "efficiency" of weight production using a stochastic frontier model with individual and county-level data which includes nearly 200,000 observations in New England between 2001 and 2010. A major contribution of this paper is extending the framework of a health production function to a stochastic production model, which provides a useful approach for researchers and policy makers to evaluate changes in food environments on health outcomes such as weight. Another contribution is the inclusion of all food environments components into a single analytical framework.

Empirical results confirm that industries such as fruit and vegetables markets and full-service restaurants are negatively associated with weight outcomes, while warehouse clubs and supercenters are positively related to weight outcomes. Supermarket and other grocery stores, convenience stores and limited-service eating places are not significantly linked with weight gain. This paper also evaluates health production efficiency and ranks them by state and by counties. These findings provide useful information to policy makers to better understand the impact of changes in food environments on obesity and health and to inform public policies to promote commercial development to that is consistent with a healthier population.

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Figure 1. Weight production efficiency indexes in Connecticut, Maine and Massachusetts

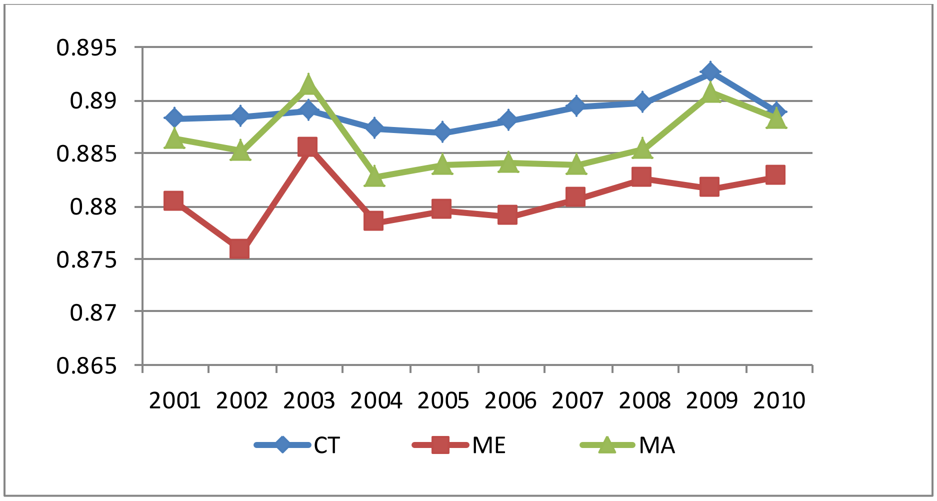

Figure 2: Weight production efficiency indexes in New England counties, 2001-2010

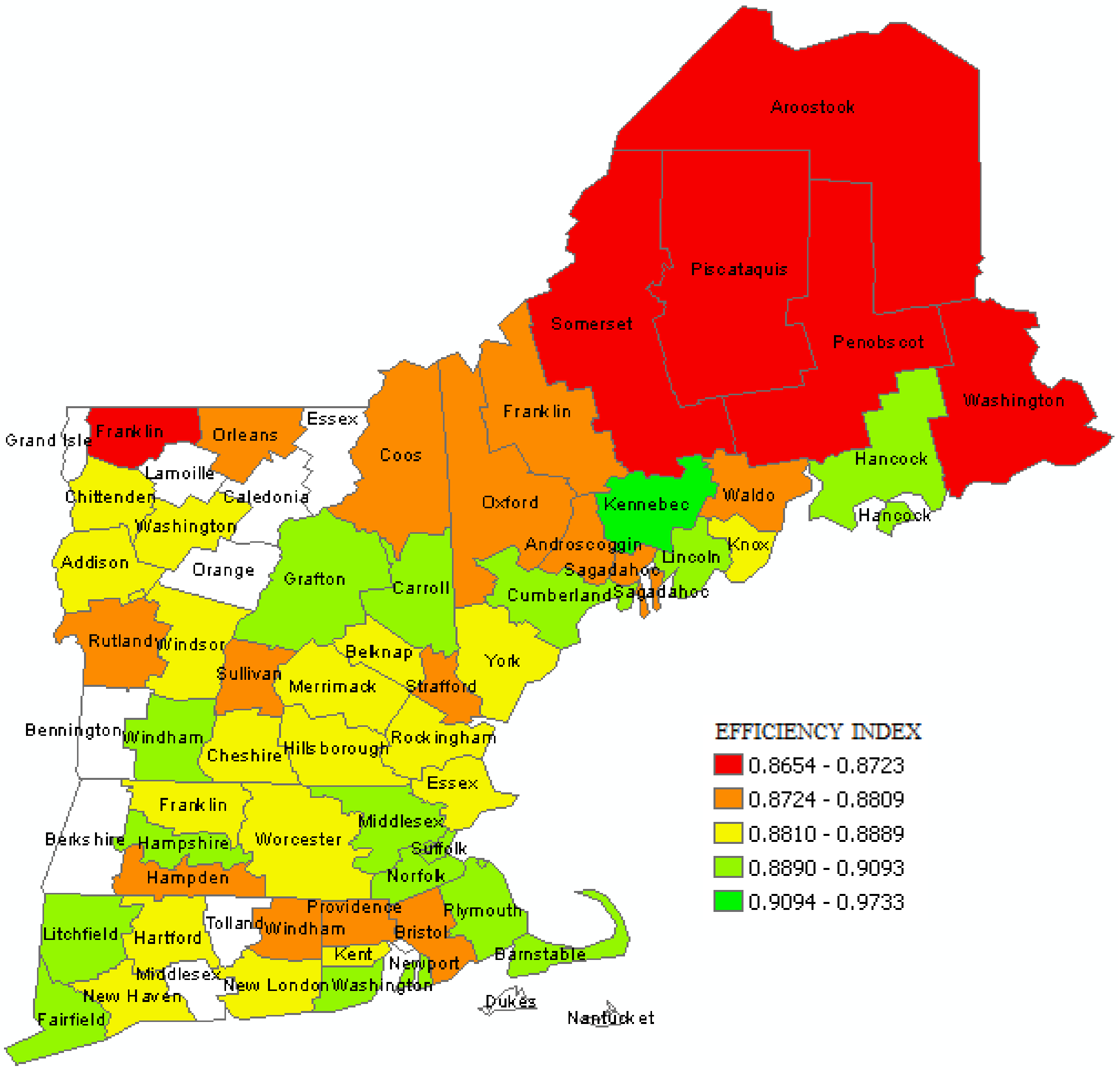

Table 1 Definition and descriptive statistics of the variables in the sample

Variable	Definition	Mean	St. dev.	Min	Max
County Level					
Supermarket	Density of supermarkets and other grocery stores (per 1000 persons)	0.251	0.104	0.965	0.832
Convenience store	Density of convenience stores (per 1000 persons)	0.186	0.070	0.042	0.579
Fruit and veg. market	Density of fruit and vegetable markets (per 1000 persons)	0.043	0.053	0.000	0.628
Supercenter	Density of warehouse clubs and supercenters (per 1000 persons)	0.069	0.087	0.000	0.521
Full-service restaurant	Density of full-service restaurants (per 1000 persons)	0.956	0.312	0.279	5.860
Limited-service rest.	Density of limited-service eating places (per 1000 persons)	0.940	0.209	0.156	2.621
Median income	Median value of income level in each county	54046	11319	26523	84250
Crime rate	Number of crimes (violence and property) per 1000 persons	25.569	10.435	0.000	133.491
Travel to work	Average minutes used on traveling to work in each county	24.359	3.083	11.100	31.900
Population density	Number of persons per 1000 square miles in each county	1.124	2.190	0.004	12.338
Individual Level					
BMI	Body mass index	26.417	4.977	1.578	89.010
Age	Age in years	50.372	15.947	18.000	90.000
Children	Number of children	0.679	1.051	0.000	10.000
Education	Education level	5.038	1.020	1.000	6.000
Income	Income level	6.151	1.925	1.000	8.000
Female	1 if female	0.577	0.494	0.000	1.000
White	1 if race is White	0.889	0.314	0.000	1.000
Hispanic	1 if race is Hispanic	0.048	0.214	0.000	1.000
Black	1 if race is Black	0.029	0.169	0.000	1.000
Asian	1 if race is Asian	0.014	0.118	0.000	1.000
Married	1 if married	0.572	0.495	0.000	1.000
Activity	1 if there is physical activity or exercise	0.724	0.447	0.000	1.000
Smoke	1 if smoked at least 100 cigarettes in entire life	0.509	0.500	0.000	1.000
Drink	1 if drank any alcohol beverage in past 30 days	0.911	0.285	0.000	1.000
Job	1 if job is sedentary	0.311	0.463	0.000	1.000
Retire	1 if retired	0.587	0.492	0.000	1.000

Note: Age2, Children2, Education2 and Income2 denote the square of these variables. They are not presented in this table.

Table 2 Parameter Estimates for the stochastic frontier model

Variable	Coefficient	Z-value	Coefficient	Z-value
Production frontier	(1)		(2)	
Age	1.029***	46.66	1.007***	44.54
Age2	-0.131***	-44.51	-0.128***	-42.38
Children	-0.007***	-8.38	-0.007***	-8.00
Children2	0.001***	5.64	0.001***	5.51
Education	0.171***	15.90	0.174***	15.83
Education2	-0.082***	-21.65	-0.085***	-22.00
Income	0.007**	2.00	0.007**	2.15
Income2	-0.004***	-3.34	-0.005***	-4.09
Female	-0.076***	-101.82	-0.076***	-99.56
White	-0.011***	-4.16	-0.011***	-4.24
Black	0.043***	12.25	0.045***	12.73
Hispanic	0.010***	3.09	0.013***	4.24
Asian	-0.090***	-22.83	-0.087***	-21.51
Married	0.007***	7.97	0.008***	8.64
Activity	-0.028***	-30.86		
Smoke	-0.004**	-6.78	-0.005***	-6.56
Drink	-0.008***	-4.61	-0.007***	-4.76
Job	0.001	0.85	0.009***	10.37
Retire	0.013***	14.95	0.013***	14.12
Constant	1.135***	26.67	1.120***	26.32
Determinants of Efficiency				
Supermarket	-0.196	-1.32	-0.138	-1.17
Convenience store	0.131	0.92	0.090	0.79
Fruit and veg. store	-0.429*	-1.90	-0.417**	-2.30
Supercenter	0.393**	1.98	0.452***	2.81
Full-service restaurant	-0.294***	-5.34	-0.238***	-5.77
Limited-service Rest.	0.054	0.80	0.064	1.18
Median income	-0.000***	-5.59	-0.000***	-5.19
Crime rate	0.002**	2.52	0.002***	2.95
Travel to work	-0.002	-1.04	-0.003	-1.14
Population density	-0.051***	-4.82	-0.049***	-5.10
Constant	-0.823***	-5.44	-0.801	-5.86
Distribution of u and v				
σ_u^2	0.213***	9.73	0.201***	10.71
σ_v^2	0.015***	107.14	0.015***	103.57
γ	0.935***	156.88	0.933***	167.42
Log likelihood function	70563.75		69850.19	
Observations	188655		189103	

Note: State fixed effects and time fixed effects are included in the model.

Table 3 Rankings of weight production efficiency in New England states during 2001-2010

Year	CT	ME	MA	NH	RI	VT
2001	0.88819	0.88029	0.88627	0.88813	0.88566	0.88145
2002	0.88838	0.87582	0.88515	0.88602	0.88525	0.88154
2003	0.88894	0.88530	0.89147	0.89067	0.88697	0.88596
2004	0.88730	0.87837	0.88277	0.88424	0.88451	0.88572
2005	0.88683	0.87957	0.88387	0.88361	0.88029	0.88221
2006	0.88808	0.87905	0.88402	0.88580	0.88061	0.88347
2007	0.88928	0.88074	0.88386	0.88338	0.88329	0.88564
2008	0.88973	0.88247	0.88534	0.88659	0.88454	0.88342
2009	0.89256	0.88168	0.89066	0.88556	0.88344	0.88731
2010	0.88887	0.88277	0.88822	0.88564	0.88125	0.88799
Mean	0.88888	0.88087	0.88614	0.88563	0.88345	0.88438

Note: Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), Rhode Island (RI), Vermont (VT)

Table 4 Rankings of weight production efficiency for New England counties during 2001-2010

State	NAME	EFFICIENCY	RANK
Maine	Kennebec	0.973299	1
Massachusetts	Suffolk	0.90926	2
New Hampshire	Carroll	0.899267	3
Massachusetts	Barnstable	0.898825	4
Connecticut	Fairfiled	0.898108	5
Massachusetts	Norfolk	0.896854	6
Rhode Island	Newport	0.895384	7
Rhode Island	Washington	0.892693	8
Connecticut	Litchfield	0.892590	9
Maine	Cumberland	0.892509	10
Massachusetts	Middelsex	0.892121	11
Maine	Lincoln	0.891893	12
Vermont	Windham	0.891428	13
New Hampshire	Grafton	0.891286	14
Massachusetts	Hampshire	0.891261	15
Maine	Hancock	0.890480	16
Massachusetts	Plymouth	0.8903524	17
New Hampshire	Rockingham	0.888885	18
Maine	Knox	0.888796	19
Vermont	Chittenden	0.887881	20
Massachusetts	Essex	0.886398	21
Vermont	Windsor	0.8861818	22
Connecticut	Hartford	0.884953	23
New Hampshire	Belknap	0.884744	24
New Hampshire	Hillsborough	0.884484	25
Rhode Island	Kent	0.884383	26
Maine	York	0.884026	27
New Hampshire	Merrimack	0.883994	28
Connecticut	New Haven	0.883705	29
Vermont	Washington	0.883648	30
Connecticut	New London	0.882923	31
Massachusetts	Franklin	0.882339	32
Vermont	Addison	0.882223	33
Massachusetts	Worcester	0.8817598	34
New Hampshire	Cheshire	0.881520	35
Rhode Island	Providence	0.880860	36
New Hampshire	Sullivan	0.880276	37
New Hampshire	Strafford	0.879951	38
Maine	Sagadahoc	0.879841	39
Maine	Franklin	0.879323	40

Massachusetts	Bristol	0.879181	41
New Hampshire	Coos	0.878182	42
Connecticut	Windham	0.877983	43
Maine	Waldo	0.877127	44
Vermont	Orleans	0.876777	45
Maine	Oxford	0.876079	46
Massachusetts	Hampden	0.875988	47
Vermont	Rutland	0.875455	48
Maine	Androscoggin	0.875013	49
Vermont	Franklin	0.872274	50
Maine	Penobscot	0.871994	51
Maine	Piscataquis	0.870101	52
Maine	Washington	0.869675	53
Maine	Aroostook	0.868992	54
Maine	Somerset	0.865413	55