Sustainable Development: Examining the Impacts of Built-Environment and Transportation on Public Health

Amir Samimi, Ph.D. Candidate
Department of Civil and Materials Engineering
University of Illinois at Chicago
842 W. Taylor Street
Chicago, IL 60607-7023
Tel: (312) 996-0962
Fax: (312) 996-2426
Email: asamim2@uic.edu

Abolfazl (Kouros) Mohammadian, Ph.D. (corresponding author)*
Assistant Professor
Department of Civil and Materials Engineering
University of Illinois at Chicago
842 W. Taylor Street
Chicago, IL 60607-7023
Tel: (312) 996-9840
Fax: (312) 996-2426
Email: kouros@uic.edu

Paper submitted for presentation in
Transport Chicago Conference 2008

ABSTRACT

Urban transportation planning and land-use policies play a pivotal role in every society and are the subject of interest in many academic fields. Creating a tool that measures the benefits and costs associated with the built environment, which includes the surrounding land-use and transportation system, would allow decision makers to choose the best option available to them when deciding on those important issues. In addition to travel time, congestion, safety, energy and environment, public health is an important subject that can be affected by transportation system. Planners are interested to know if transit usage could decrease the risk of heart attack, high blood pressure, or obesity. They also like to know how different the health conditions of people living in urbanized areas are from those living in rural areas, or how pedestrian-friendly environments could decrease the chance of asthma infection.

The primary objective of this study is to develop models for different health-related variables including General Health, High Blood Pressure, High Blood Cholesterol, Asthma, Obesity, and Heart Attack to investigate the effect of transportation, land-use, and the built environment variables along with demographic and socio-economic factors on the healthiness of people. The results of the analysis showed that increasing the transit-use and decreasing the auto-use have significant positive impact on all the health variables except for asthma. In addition to the transit-oriented development, making the environment more pedestrian friendly (e.g., smaller block size) could motivate people to be more physically active in their daily routines and have a healthier lifestyle.

Key Words: Health, Transportation, Built Environment, Land-Use Planning, Physical Activity, Binary Probit Model.

1. INTRODUCTION

Urban transportation planning and land-use policies play a significant role in every country around the world, especially in the United States. The average family living in the United States continues to drive more and more every year while land is consumed by the growing suburbs. In 2005 Americans flooded the highway system with their personal vehicles traveling 2.67 trillion person-miles (1). Americans drove their personal vehicles for a wide variety of purposes such as traveling to work, shopping, taking children to daycare, visiting friends and family, going on vacations, and for many other purposes. In the last decade total vehicle miles for all modes of transportation, in the US, grew by nearly 600 billion miles from 2.4 trillion in 1994 to close to 3 trillion in 2004 (1). This huge number shows the importance of considering different aspects of this essential and extensive system in any society. Having a good measure for the adverse consequences of our transportation system, policy makers would be able to better estimate the true cost of their decisions, and take the most beneficial strategy.

According to the literature, the three most important consequences of a transportation system are: "Travel Times and Congestion", "Safety", and "Energy and Environment". This paper will introduce and explore the potential effects that land-use planning and the transportation system has on a population's health. Do auto-use, transit-use, block size, road density, population density, etc affect the health of a population or community? Though at the first glance, transportation, land-use and built environment variables might look irrelevant to the health of a population, the paper aims at finding an acceptable correlation between the health of the population and the surrounding land-use and transportation system.

There has been a considerable effort to study the relationship of "health-related variables" and "transportation system, land-use and build environment components". Different types of models have been developed in the literature to address various aspects of this issue. Among the first studies Wachs and Kumagai (2) showed that accessibility to the economic, recreational, service and social opportunities within a region is an important component of the quality of life within the region. Several suggestions for the study of physical accessibility as a social indicator are also included in their paper. Furthermore, researchers have mainly focused on the illustration of complex relationships that affect health care access. Phillips et al (3) believe that poor households face barriers to health care and are at greater risk of poor health outcomes. They suggest that health care planners and policy makers should target scarce resources to areas in greatest need of help. Also, Hendryx et al (4) show that people who live in metropolitan statistical areas featuring higher levels of social capital report fewer problems accessing health care.

Jones et al (5) exclusively focused on asthma and found that there is a significant tendency for asthma mortality to increase with travel time to a hospital. The study concluded that the number of asthma related deaths could be dramatically reduced with better access to hospital facilities. Many studies have examined if there is an association between body mass index (BMI) and the built environment. The study conducted by McCann and Ewing (6) is one of the most comprehensive studies on this topic. This study examined obesity at the county level and used data from the Center for Disease Control. They concluded that people residing in sprawling counties have a higher level of obesity than people residing in non-sprawling counties. Also, Sööt et al (7) found that neighborhood factors, such as high levels of education and high home values, correlate with BMI.

Boer et al (8) looked into the effect of neighborhood design guidelines on encouraging people to have more walking trips. They found that walking trips correlates with the number of businesses, housing density, and intersection density. Furthermore, a committee consisting of 14 experts on physical activity, health, transportation, and land-use was formed by the Transportation Research Board (TRB) and the Institute of Medicine (IOM) to study the relationship between the built environment and the physical activity levels of the U.S. population in the year 2005 (9). The report discusses the limitations of the current literature on the subject and provides recommendations on how to improve the built environment to promote a more active lifestyle. It also noted that many policies already exist which encourage physical activity through improving the built environment, although further study is required to determine which factors impact a person's physical activity level and health outcome the most. A small number of other studies have been performed on this subject, but not all of them can be reviewed in this paper.

The primary objective of this study is to develop models for different health-related variables with built environment, land-use, and transportation components, in addition to demographic and socio-economic variables.

This paper is structured in six sections. Section 2 briefly explains modeling framework of this study. Section 3 describes the datasets used. Section 4 presents the process of development of the models and estimation results. Section 5 analyzes the results for binary probit models estimation. Finally, section 6 presents the conclusion, followed by the discussion.

2. MODELING FRAMEWORK

Recognition and growing concerns over the health of the population has become a national issue. Poor diet and inadequate exercise are the accepted causes which lead to a poor health condition. Other factors that could contribute to health problems, such as the built environment or culture, are currently being explored. Transportation engineering and many other disciplines have studied many different factors that could lead to poor health.

In order to develop a model for predicting the health condition of a population, two categorizations are unavoidable. First of all, various types of disease should be determined and a specific health-related variable should be targeted, since different illnesses could have diverse causes. Secondly, the cause on the illness should be categorized in a way that the most influential factors such as poor diet and insufficient exercise are included in the main model. No one doubts that built environments and land-use components have a lower level effect on health, comparing to unhealthy diet and inactivity. So a key part of modeling is to include the main causes in the model and improve it by adding more factors. For instance, if a model has auto-use without income and education, the results could be misleading. Because the reason that people with more auto-use are healthier, is because of their different income group, not because they have higher auto-use. Or similarly, if transit-use has a positive coefficient in a specific disease model, it could be because of the fact that people with lower income tends to have more transit trips.

Next step is choosing a proper model type for the data. The choice of model depends on the available data type. For a continuous dependent variable such as BMI, ordinary least square method (OLS) could be a convenient way to proceed. This has been effectively used in the study done by Sööt et al (7). But for a binary dataset, if the model is estimated with OLS, some of the estimated values would lie outside the range 0-1 and the residuals will be heteroskedastic (10). A better way to solve the problem would be a binary probit model that resolves this issue.

Binary probit has been widely used in many fields. To have a brief introduction of binary probit model, suppose ε_{in} and ε_{jn} are both normally distributed with zero means, σ^2_i and σ^2_j variances, and σ_{ij} covariance. So $\varepsilon_{jn} - \varepsilon_{in}$ is also normally distributed with mean zero and variance $\sigma^2 = \sigma^2_i + \sigma^2_j - 2\sigma_{ij}$. The probability of choosing i over j could be modeled in a probit framework, as shown in Equation 1 (11).

$$
\begin{aligned}
P_n(i) = \Pr(\varepsilon_{jn} - \varepsilon_{in} \le V_{in} - V_{jn}) &= \int_{\varepsilon=-\infty}^{V_{in}-V_{jn}} \frac{1}{\sqrt{2\pi}} \exp\left[\frac{-1}{2}\left(\frac{\varepsilon}{\sigma}\right)^2\right] d\varepsilon \\
&= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(V_{in}-V_{jn})/\sigma} \exp\left[\frac{-u^2}{2}\right] du = \Phi\left(\frac{V_{in}-V_{jn}}{\sigma}\right)
\end{aligned}
\tag{1}
$$

where Φ (.) denotes the standardized cumulative normal distribution and V_{in} represents the utility of alternative i for decision maker n. In the model above, $1/\sigma$ is the scale of the utility function which can be set to any positive value, usually $\sigma = 1$ (11).

3. DATA

The Behavioral Risk Factor Surveillance System (BRFSS) was the primary data source used for this study (12). Demographic, socio-economic, and health-related information were taken from BRFSS 2005 for more than 300,000 individuals. The transportation, land-use, and built environment variables, at the county-level, were then appended to each observation. Since the zip code for each individual in the dataset was not accessible to the public, the lowest level of geography available for each record that was used in this study was the person's county of residence.

Other data sources used in this study include the National Household Travel Survey (NHTS 2001) (13), the Census Transportation Planning Package (CTPP 2000), and the Census 2000 TIGER/Line GIS data files. The definitions and variables that reflects the pedestrian environment and transit usage was borrowed from the Mohammadian and Zhang (14) study. And more detailed description of the datasets used in this study is discussed in the coming sections.

3.1. BRFSS

The main dataset used in this study was the BRFSS, which is rated as the world's largest, on-going telephonic health survey system. Fifty state health departments as well as those in the District of Columbia, Puerto Rico, Guam, and the U.S. Virgin Islands, with support from the Centers for Disease Control and Prevention, have tracked the health conditions and risk behaviors in the U.S. since 1984. BRFSS includes data regarding health-related issues such as blood pressure, blood cholesterol, asthma, diabetes, stress, obesity, nutrition, physical activity, and more (12). The survey, which is conducted by telephone, targets the adult population (18 years of age or older) and collects information on an individual's health and other behavioral factors. Although, approximately 95 percent of American households have telephones, no direct method of balancing for non-telephone coverage is used by the BRFSS (12). A brief descriptive analysis of the variables collected from the BRFSS is reported in Table 1.

3.2. Transportation, Land-use and Built Environment

An extensive GIS effort was undertaken to generate county-level variables for transportation, land-use, and built environment. These factors were calculated from different data sources including the NHTS 2001, the CTPP 2000, and the Census 2000 TIGER/Line GIS data files, which are summarized in Table 1. Similar to the Mohammadian and Zhang (14) study, population density was directly extracted from the NHTS 2001, and other variables reflecting the pedestrian environment and transit usage were estimated by matching street network and census tract shape-files in a GIS environment. In order to determine whether each census tract is transit friendly, Mohammadian and Zhang introduced a transit-use measure which estimated the proportion of transit users to the total number of workers using CTPP 2000 data. In addition to this measure, another factor for transit-use was determined for this study, which is the proportion of transit users to the whole population. Similar measures were defined for auto-use. Also, Mohammadian and Zhang introduced intersection density, road density, and block size as measures to determine how pedestrian friendly the neighborhood is.

4. HEALTH-RELATED BINARY MODELS

This section describes the development process of the binary choice models for *General Health*, *Blood Pressure*, *Blood Cholesterol*, *Asthma*, *Obesity* and *Heart Attack*. More than 300,000 observations were imported into the Limdep Econometric Software (15) environment, which was used for parameter estimation. In order to specify an appropriate model for each case, binary probit and logit models with different utility functions were tested. The variables, which entered the utility functions include: demographic variables, socio-economic attributes, transportation, land-use, and built environment components. The best models were chosen based on the significant coefficients with rational signs for all the covariates and different measures for goodness of fit for the whole model including chi-square, Akaike I.C. and Ben-Akiva/Lerman values. Each model is described in detail in the following section.

4.1. Fit Measures for a Binary Choice Model

The success rate of the model presents its prediction power which implies the overall ability of the model to estimate the dependant variable. This measure is highly important and informative. A variety of fit measures are offered for binary choice models, including Estrella, Efron, McFadden, Ben-Akiva/Lerman, Cramer, Veall and Zimmermann, $R^2{}_{ML}$, Akaike, and Schwarz. There is no specific recommendation for those measures, however Yagi (16) suggests that some measures such as Akaike not only reward goodness of fit, but also include a penalty that is an increasing function of the number of parameters, and these measures seem to be more reliable.

For this study, the general ability of each model in predicting the dependant variable, in addition to other indicators, is presented. For each model, chi-square, Akaike, and Ben-Akiva/Lerman values are reported and the selection of the best model for each dependant variable is based on the last two measures. As the values for Akaike decrease and the Ben-Akiva/Lerman values increase, goodness of fit for the whole model improves. To have a better sense of these two measures, suppose y_i is the i^{th} observed value for the binary 0-1 variables and F_i is the predicted probability for a given utility function. If K represents the number of coefficients in the model and n is the number of observations, Ben-Akiva/Lerman and Akaike values will be computed using Equation (2) and (3), respectively (15).

$$\text{Ben-Akiva/Lerman} = \frac{1}{\mathrm{n}}\sum_{i=1}^{n}(1-y_i)(1-F_i)+y_iF_i \tag{2}$$

$$\text{Akaike} = \frac{2}{\mathrm{n}}\left(K-\sum_{i=1}^{n}y_i\log F_i+(1-y_i)\log(1-F_i)\right) \tag{3}$$

4.2. General Health Model

General Health is a binary 0-1 variable in the database that shows the general feeling of a person about his/her health. One represents good health condition and zero stands for fair or poor conditions. After excluding all the observations with missing values, binary probit and logit models with maximum likelihood estimation method were run for 263,390 observations. *Income*, *Exercise*, *Children*, *Transit-use*, and *Block-size* turned out to be the most influential variables on *General Health*; however moderate physical activity was competing very closely with exercise. The final model which is shown in Equation 4 could predict 84 percent of the observations correctly, which presents a promising prediction potential.

$$\begin{aligned}\Phi\left(\mathrm{P}_{\text{General Health}}\right) = {} & -0.50+0.42\ \text{Transit Use}_1+0.12\ \text{Block Size}+0.29\ \text{Income} \\ & +0.59\ \text{Exercise}+0.27\ \text{Children}\end{aligned} \tag{4}$$

More details of this model, including fit measures for the model, standard errors and significances of all the parameters are summarized in Table 2.

4.3. High Blood Pressure Model

Risk of serious health problems such as heart attack and stroke will be heightened by high blood pressure and typically develops without signs and will eventually affects nearly everyone. According to the American Heart Association, there is no specific cause for 90% of all reported cases of high blood pressure, though 10 percent are caused by an underlying condition. Age, race, family history, excess weight, inactivity, tobacco use, and stress are recognized as the leading factors to high blood pressure (18).

As described in Table 1, *Blood Pressure* is a binary 0-1 variable that shows whether the individual has high blood pressure. After excluding all the observations with missing values, the number of observations dropped to 250,178. More than 90 binary probit and logit models with maximum likelihood estimation method were developed and Equation 5 was chosen as the best one. *Auto-use*, *Population Density*, *Road Density*, *Income*, *Age*, and *Moderate Physical Activity* are introduced as the leading variables to high blood pressure.

$$\begin{aligned}\Phi\left(P_{\text{Blood Pressure}}\right) = &-2.59 + 0.79\ \text{Auto Use}_2 + 0.58\text{E-05 Population Density} \\ &+ 0.95\text{E-02 Road Density} - 0.08\ \text{Income} + 0.03\ \text{Age} \\ &- 0.18\ \text{Moderate Physical Activity}\end{aligned} \tag{5}$$

Equation 5 could predict 73 percent of the observations correctly, which is satisfactory. Fit measures for the model, standard errors, and significances of all the parameters are summarized in Table 3.

4.4. High Blood Cholesterol Model

High blood cholesterol increases the fatty deposits in arteries, which eventually could lead to a heart attack or brain stroke. High cholesterol could be controlled with a healthy diet, regular exercise, and other lifestyle changes; on the other hand, inactiveness, obesity, unhealthy diet, smoking, high blood pressure, and diabetes are the main causes of high blood cholesterol (17).

Similar to *Blood Pressure*, *Blood Cholesterol* is another binary 0-1 variable in the database that shows whether the person has high blood cholesterol. After excluding the observations with a missing value, around 150 binary probit and logit models with maximum likelihood estimation method were run for 217,868 observations. As shown in Equation 6, *Auto-use*, *Road Density*, *Population Density*, *Income*, *Age*, *Children*, and *Sex* turned out to be the most influential variables.

$$\begin{aligned}\Phi\left(P_{\text{Blood Cholesterol}}\right) = &-1.56 + 0.47\ \text{Auto use}_2 + 0.002\ \text{Road Density} \\ &+ 0.52\text{E-05 Population Density} + 0.018\ \text{Age} \\ &- 0.132\ \text{Children} - 0.033\ \text{Income} + 0.11\ \text{Sex}\end{aligned} \tag{6}$$

The final model in Equation 6 could predict 62 percent of the observations correctly, which is acceptable. More details of this model, including fit measures for the model, standard errors, and significances of all the parameters are summarized in Table 4.

4.5. Asthma Model

According to the Mayo Foundation for Medical Education and Research, nearly 14 million adults and 6 million children in the U.S. have asthma. Asthma is more common in boys than in girls, but after puberty asthma is more common in females. Living in large urban areas, which may increase exposure to environmental pollutants, is introduced as the major factor that increases the risk of asthma infection (17).

Whether or not people have asthma, is determined by a binary 0-1 variable in the dataset, called *Asthma*. After excluding the observations with a missing value, around 200 binary probit and logit models with maximum likelihood estimation method were run for 263,765 observations. As shown in Equation 7, *Block-size*, *Transit-use*, *Sex*, *Income*, and *Exercise* are the most influential variables.

$$\begin{aligned}\Phi\left(P_{\text{Asthma}}\right) = &-0.77 - 0.19\ \text{Block size} + 0.13\ \text{Transit use}_2 - 0.2\ \text{Sex} \\ &- 0.05\ \text{Income} - 0.09\ \text{Exercise}\end{aligned} \tag{7}$$

The final model in Equation 7 could predict 87 percent of the observations correctly, which is excellent. More details of this model, including fit measures for the model, standard errors, and significances of all the parameters are summarized in Table 5.

4.6. Obesity Model

The Center for Disease Control and Prevention (18) has defined obesity as having a BMI greater than 30. Having a BMI greater than 30 would result in an individual having a high proportion of body fat. Obesity increases the risk of high blood pressure, diabetes, and many other serious health issues and unfortunately, about one third of American adults are considered to be obese. Although there are genetic influences on body weight, regular physical activity is a recognized way of preventing obesity. Poor diet, inactivity, pregnancy, and medical problems are major accepted contributing factors to weight gain and obesity (17).

BMI is computed from the weight and height of an individual and is coded as a binary 0-1 variable to identify if the person has a BMI greater than 30. Similar to other variables, one stands for the obese persons and zero otherwise. More than 100 binary probit and logit models with maximum likelihood estimation method were run for 293,224 observations. As shown in Equation 8, *Auto-use*, *Transit-use*, *Road Density*, *Moderate Physical Activity*, *Education*, and *Income* are the leading variables for *Obesity*.

$$\begin{aligned}\Phi\left(\mathrm{P}_{\text{Obesity}}\right) = &-0.51 + 0.27\ \text{Auto use}_2 - 0.90\ \text{Transit use}_1 + 0.004\ \text{Road Density} \\ &- 0.32\ \text{Moderate Physical Activity - 0.101 Education - 0.049 Income}\end{aligned} \tag{8}$$

The final model in Equation 8 could predict 75 percent of the observations correctly, which is considered as a good model fit. More details of this model, including fit measures for the model, standard errors, and significances of all the parameters are summarized in Table 6.

4.7. Heart Attack Model

A heart attack is caused by the loss of blood and oxygen to an area of the heart muscle. The usual cause of a heart attack is a blood clot that blocks the coronary artery. Smoking, high blood pressure, high blood cholesterol, inactivity, obesity, diabetes, stress, family history, and alcohol are the primary factors that increase the risk of a heart attack (17).

Using a 0-1 variable for heart attack, a binary probit model shown in Equation 9, is calibrated by 279,295 observations. The model clearly shows the importance of transit usage and the negative effects of auto usage in increasing the risk of having a heart attack. Other than those variables, population density and age tend to increase the risk of heart attack; however, regular moderate physical activity and marriage decrease the risk of heart attack.

$$\begin{aligned}\Phi\left(\mathrm{P}_{\text{Heart Attack}}\right) = &-3.80 + 0.62\ \text{Auto use}_2 - 0.96\ \text{Transit use}_1 \\ &+ 0.91\text{E - 05 Population Density} + 0.03\text{Age} \\ &- 0.15\ \text{Moderate Physical Activity - 0.03 Married}\end{aligned} \tag{9}$$

The model above describes about 95% of the observations correctly, which represent a perfect model. More details of this model, including fit measures for the model, standard errors, and significances of all the parameters are summarized in Table 7.

5. ANALYSIS OF THE RESULTS

As discussed earlier, almost all the parameters in the models above are statistically significant at the 99 percent confidence level and the prediction capability of all models is acceptable. A general discussion on the effect of land-use, transportation, and the built environment variables is presented in the next part and the marginal effects are also analyzed.

5.1. General Discussion

In the *General Health*, *Blood Pressure*, *Blood Cholesterol*, *Obesity*, and *Heart Attack* models, *Auto-use* and *Transit-use* have negative and positive effects on health, respectively. Equation 8 and 9 showed that switching from automobile mode to transit mode could increase the chance of being healthier, in terms of obesity and heart attack. This claim is not true in the case of *Asthma* model, probably since using transit mode requires more walking trips than the automobile mode, which could be a negative factor for people with asthma. Also, the bigger the block size, the more chance for being healthy. Equations 4 and 7 confirm that people living in neighborhoods with larger block size have higher chance of being healthy and less chance for asthma infection. In addition, *Population Density* and *Road Density* showed a negative correlation with the level of healthiness. Equations 5, 6, 8, and 9 suggest people living in the urbanized areas with more population or higher road density have a greater chance of having high blood pressure, high blood cholesterol, obesity, and/or a heart attack.

Other than transportation, land-use, and built environment variables, *Income*, *Exercise*, and *Children* showed a positive correlation with *General Health*. *Income* and *Moderate Physical Activity* had a negative correlation with *Blood Pressure*, while *Age* had a positive relationship. In the sixth equation, *Children* and *Income* had a positive effect on *Blood Cholesterol*, while *Age* had a negative correlation; also females seem to have a lower chance for high blood cholesterol development. Similar to previous inferences, *Income* and *Exercise* could decrease the chance of asthma infection; however males have a lower chance for it. As expected, *Moderate Physical Activity*, *Income* and *Education* have a negative correlation with *Obesity*; and similarly, *Moderate Physical Activity* and being *Married* has a positive effect on decreasing heart attack risk while *Age* has a positive correlation.

5.2. Marginal Effects Analysis

In order to quantify the effects of transportation, land-use, and built environment variables on the health-related variables, marginal effect analysis is necessary. It reflects how the changes in the independent variable (e.g., *Transit-use*) affect the dependent variable (e.g., *Obesity*). Marginal effects calculation for a binary choice model is shown in Equation 10 (15).

$$\frac{\partial E[y|\mathrm{x}]}{\partial \mathrm{x}} = \frac{\partial F(\beta'\mathrm{x})}{\partial \mathrm{x}} = \frac{dF(\beta'\mathrm{x})}{d\beta'\mathrm{x}}\beta = F'(\beta'\mathrm{x})\beta = f(\beta'\mathrm{x})\beta \qquad (10)$$

Vector of marginal effects is a scalar multiple of the coefficient vector (β) and could be calculated at any data point. The scale factor, $f(\beta' x)$, is the density function, which is computed at the vector of means of the observations. Marginal costs are summarized in Table 8.

As shown in Table 8, the marginal cost of transportation, land-use, and built environment variables on health-related variables are considerable. Every percent increase in *Transit-use* will decrease *Heart Attack* by 0.07 percent and *Obesity* by 0.29 percent. Every percent increase in *Transit-use* would improve *General Health* by 0.09 percent however it will increase the chance of *Asthma* infection by 0.03 percent. Every unit decrease in *Auto-use* would reduce the chance of *High Blood Pressure* and *High Blood Cholesterol* by 0.26 and 0.18 percent, respectively.

Switching from personal vehicles to transit mode could have substantial effects on *General Health*, *Blood Pressure*, *Blood Cholesterol*, *Obesity*, and *Heart Attack* however, it has a small negative effect on *Asthma*. Generally, it can be concluded that encouraging people to switch from automobile mode to transit mode could have very positive outcomes in the health condition of the society.

For other variables such as *Block-Size*, *Population Density*, and *Road Density* the expected results were obtained. Generally, living in neighbourhoods with larger block size, less population, and smaller road density had positive effects on health-related factors. Every percent increase in *Block-Size* will improve the chance of *General Health* by 0.02 percent and decrease the risk of *Asthma* infection by 0.04 percent. Similarly, every 100 percent increase in *Road Density* would increase the chance of *High Blood Pressure*, *High Blood Cholesterol*, and *Obesity* by 0.3, 0.07 and 0.1 percent, respectively. In a similar way, increased *Population Density* could result in higher chance of *High Blood Pressure*, *High Blood Cholesterol*, and *Heart Attack* risk.

6. CONCLUSIONS

In addition to travel time, congestion, safety, energy, and environment, other important issues such as people's health should be considered as a side effect of the transportation system. Having a good measure for diverse consequences of land-use, transportation, and the built environment alternatives on the health condition of people, will provide decision makers with a powerful tool to estimate the true costs of alternative options in policy analysis and decision making process.

In this paper, a combination of demographic, socio-economic, transportation, land-use, and built environment variables were used to develop models for predicting health-related variables. Six binary variables for *General Health*, *High Blood Pressure*, *High Blood Cholesterol*, *Asthma*, *Obesity*, and *Heart Attack* were defined and the associated binary probit models were reported. In addition to demographic and socio-economic variables, *Auto-use*, *Transit-use*, *Block-Size*, *Population Density*, and *Road Density* were influential on the healthiness of the people. Switching from auto-use to transit-use and making the environment more pedestrian friendly could have substantial positive effects on people's level of health. Every percent increase in *Transit-use* would decrease the risk of *Obesity* and *Heart Attack* by 0.29 percent and 0.07 percent, respectively. It also increases the chance for a person to be generally healthy by 0.09 percent. This implies that if, for example, share of transit mode choice in an urban area is increased from 2% to 4%, the risk of obesity and heart attack will be decreased by 29% and 7% and people will be 9% healthier. Similarly, every percent decrease in auto usage could decrease the risk of high blood pressure and high blood cholesterol by 0.26 percent and 0.18 percent, respectively.

It was shown that neighborhoods that are considered more pedestrian friendly could motivate people to walk more and be healthier. In fact, changing the built environment and making the neighborhoods more pedestrian friendly and transit friendly could encourage people to increase the physical activity on their daily routine that can eventually lead to significant positive effects on the health conditions of the whole society. It will also decrease the burden of medical services expenditure on the general public.

ACKNOWLEDGEMENT

I would like to thank my friend, Yong-Ping Zhang for providing part of the data. Also I am extremely thankful for my colleagues, Todd Schmidt and Inshu Minocha, supports in the literature review and edition part.

REFERENCES

1. US Department of Transportation, Transportation Statistics Annual Report, December 2006.
2. Wachs, M., and Kumagai, T.G., "Physical Accessibility as a Social Indicator", Socio-Economic Planning Sciences, Vol. 7, October 1973, pp. 437-456.
3. Phillips, R.L., Parchman, M.L., and Miyoshi, T.J. "Using geographic information systems to understand health care access", Arch Fam Med, Vol. 9, November / December 2000, pp. 971-978.
4. Hendryx, M. S., Ahern, M. M., Lovrich, N. P., and McCurdy, A. H. "Access to Health Care and Community Social Capital", HSR: Health Services Research 37:1, February 2002.
5. Jones, A.P., Bentham, G., and Horwell, C. "Health Service Accessibility and Deaths from Asthma", International Journal of Epidemiology, Vol 28, 1999, pp. 101-105.
6. McCann, B., and Ewing, R. "Measuring the Health Effects of Sprawl", Smart Growth America, Surface Transportation Policy Project, September, 2003, pp 41.
7. Sööt, S., Dirks, L., Metaxatos, P., Mohammadian, A., Yanos, G., and Zhou, J., "Are Sprawl and Obesity Related? Evidence from the Chicago Area" Metropolitan Transportation Support Initiative (METSI) Working Paper, January 2006.
8. Boer, R., Zheng Y., Overton A., Ridgeway G.K., and Cohen D.A. "Neighborhood Design and Walking Trips in Ten U.S. Metropolitan Areas", American Journal of Preventive Medicine, Vol. 32, No. 4, April 2007, pp. 298-304.
9. Transportation Research Board, Institute of Medicine of the National Academies "Does the Built Environment Influence Physical Activity? Examining the Evidence", Transportation Research Board Special Report 282, 2005.

10. Stokes, H.H., "Specifying and Diagnostically Testing Econometric Models (Edition 2)", Greenwood Publishing Group, Inc., 2006.

11. Ben-Akiva, M., Lerman, S.R. "Discrete Choice Model: Theory and Application to Travel Demand", the MIT Press, Cambridge, Massachusetts, 1985.

12. National Center for Chronic Disease Prevention and Health Promotion, Behavioral Risk Factor Surveillance System 2005, http://www.cdc.gov/brfss/, Accessed 15 July, 2007.

13. Federal Highway Administration (FHWA). National Household Travel Survey (NHTS 2001), http://nhts.ornl.gov/download.shtml, accessed 15 July, 2007.

14. Mohammadian, A., Zhang, Y. "Investigating the Transferability of National Household Travel Survey Data", forthcoming in the Journal of the Transportation Research Record, 2007.

15. Greene H. William, "LIMDEP Version 8.0 User's Manual", Econometric Software Inc., Plainview, NY, USA, 2002.

16. Yagi, Sadayuki, "An Activity-Based Microsimulation Model of Travel Demand for Transportation Policy and Impact Analysis", Ph.D. Thesis, Department of Civil and Materials Engineering, University of Illinois at Chicago, 2006.

17. Mayo Foundation for Medical Education and Research, Tools for Healthier Lives, http://www.mayoclinic.com/ , Accessed July 19, 2007.

18. Center for Disease Control and Prevention, Defining Overweight and Obesity, web article at http://www.cdc.gov/nccdphp/dnpa/obesity/defining.htm**,** accessed July 25, 2007.

List of Tables

TABLE 1 Variables Used in the Analysis and Sample Means and Standard Deviations

Variable	Definition	Mean	Std. Dev.
BRFSS			
State	State federal information processing standards code	32.910	15.42
Citycode	The county in which the individual live	62.770	75.44
Sex	0: female / 1: male	0.380	0.486
Age	Individual's age in years	51.490	17.10
Marital	0: Living alone / 1: Otherwise	0.550	0.498
Children	0: No child / 1: one or more children	0.335	0.472
Height	Individual's height in inches	66.570	4.043
Weight	Individual's weight in pounds	171.97	42.05
Education	1: Attend in or graduate from college or technical school / 0: Otherwise	0.601	0.490
Income	Annual income / 10,000	3.560	1.453
Exercise	1: If the person participated in any physical activities or exercises, other than the regular job, during the past month. / 0: Otherwise	0.750	0.435
Modpact	1: If the person did moderate activities for at least 10 minutes at a time, that causes small increases in breathing or heart rate, in a usual week. / 0: Otherwise	0.470	0.499
General Health	1: If the person's general health is in excellent or good condition/ 0: Otherwise	0.820	0.383
Blood Pressure	1: If the person have been told he/she has high blood pressure by a doctor, nurse, or other health professional. / 0: Otherwise	0.310	0.464
Blood Cholesterol	1: If the person has had his/her cholesterol checked and have been told by a doctor, nurse, or other health professional that it was high. / 0: Otherwise	0.390	0.488
Asthma	1: If the person has been told he/she has asthma / 0: Otherwise	0.130	0.335
Obesity	1: If BMI = Weight(kg)/Hieght^2(m) > 30 / 0: Otherwise	0.250	0.433
Heart Attack	1: If the person has been told to have a heart attack / 0: Otherwise	0.051	0.221
Transportation / Land-use / Built Environment			
County	County FIPS	-	-
Length	Road length for each county	2008	2042
Area	County area in square miles	1109	3599
Intersection	Number of intersections within each county	8870	10935
Population	Population of each county	88560	288979
Workers	Number of workers 16+yrs old in each county	40110	126835
Autouse	Auto usage	35246	107089
Transituse	Transit usage	1837	17989
Road_den	Road density (road length/area)	3.05	4.12
Interden	Intersection density	17.7	29.1
Block Size	Road length/number of intersections	0.275	0.358
Popdensity	County population density	263.9	1653.0
Autouse1	Auto usage/ population	0.388	0.064
Transituse1	Transit usage/ population	0.004	0.012
Autouse2	Auto usage/ workers	0.898	0.072
Transituse2	Transit usage/ workers	0.009	0.028

TABLE 2 Binary Probit Model Results for "General Health"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	- 0.501	0.011	-44.608	0.000
Transituse1	0.418	0.112	3.715	0.000
Blocksize	0.118	0.036	3.230	0.001
Income	0.288	0.002	132.857	0.000
Exercise	0.593	0.007	89.353	0.000
Children	0.267	0.007	38.554	0.000
Fit Measures				
Log likelihood function	-102683.8	Ben./Lerman		0.758
Restricted log likelihood	-120863.3	Akaike I.C.		0.780
Chi squared	36358.9	Prob[ChiSqd > value]		0.000

TABLE 3 Binary Probit Model Results for "Blood Pressure"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	-2.585	0.052	-49.298	0.000
Autouse2	0.792	0.054	14.676	0.000
Popdensity	0. 577E-05	0. 12E-05	4.751	0.000
Road_den	0.953E-02	0.001	10.075	0.000
Income	-0.080	0.002	-40.619	0.000
Age	0.032	0. 18E-03	173.874	0.000
Modpact	-0.179	0.006	-31.462	0.000
Fit Measures				
Log likelihood function	-132380.2	Ben./Lerman		0.647
Restricted log likelihood	-153381.2	Akaike I.C.		1.058
Chi squared	42002	Prob[ChiSqd > value]		0.000

TABLE 4 Binary Probit Model Results for "Blood Cholesterol"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	-1.557	0.052	-29.94	0.000
Autouse2	0.476	0.053	9.003	0.000
Road_den	0.002	0. 93 E-03	2.150	0.031
Popdensity	0.52E-05	0.11E-05	4.528	0.000
Age	0.018	0.21 E-03	81.829	0.000
Children	-0.132	0.007	-18.481	0.000
Income	-0.033	0.002	-16.207	0.000
Sex	0.114	0.006	19.879	0.000

Fit Measures			
Log likelihood function	-138458.1	Ben./Lerman	0.555
Restricted log likelihood	-145572.1	Akaike I.C.	1.271
Chi squared	14227.94	Prob[ChiSqd > value]	0.000

TABLE 5 Binary Probit Model Results for "Asthma"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	-0.775	0.012	-65.803	0.000
Blocksize	-0.187	0.037	-5.049	0.000
Transituse2	0.126	0.047	2.667	0.008
Sex	-0.202	0.007	-30.717	0.000
Income	-0.051	0.002	-23.415	0.000
Exercise	-0.094	0.007	-12.931	0.000

Fit Measures			
Log likelihood function	-100788.1	Ben./Lerman	0.776
Restricted log likelihood	-101859.3	Akaike I.C.	0.764
Chi squared	2142.455	Prob[ChiSqd > value]	0.000

TABLE 6 Binary Probit Model Results for "Obesity"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	-0.514	0.078	-6.604	0.000
Autouse2	0.267	0.085	3.144	0.002
Transituse1	-0.899	0.318	-2.824	0.005
Road_den	0.004	0.001	3.208	0.000
Modpact	-0.318	0.006	-55.888	0.000
Education	-0.101	0.006	-16.347	0.000
Income	-0.049	0.002	-23.645	0.000
Fit Measures				
Log likelihood function	-134606.2	Ben./Lerman		0.627
Restricted log likelihood	-137331.0	Akaike I.C.		1.116
Chi squared	5449.6	Prob[ChiSqd > value]		0.000

TABLE 7 Binary Probit Model Results for "Heart Attack"

Variable	Coefficient	Standard Error	t-stat	P[|Z|>z]
Constant	-3.785	0.121	-31.247	0.000
Autouse2	0.618	0.128	4.827	0.000
Transituse1	-0.963	0.425	-2.269	0.023
Popdensity	0.91E-05	0.21E-05	4.273	0.000
Age	0.029	0.29E-03	100.446	0.000
Modpact	-0.151	0.009	-16.979	0.000
Marital	-0.030	0.009	-3.434	0.001

Fit Measures			
Log likelihood function	-49487.23	Ben./Lerman	0.909
Restricted log likelihood	-56294.73	Akaike I.C.	0.353
Chi squared	13615.01	Prob[ChiSqd > value]	0.000

TABLE 8 Marginal Effects for Transportation, Land-use and Built Environment Variables

Variable	Auto-Use	Transit-Use	Block-Size	Road Density	Population Density
General Health	-	0.090	0.025	-	-
Blood Pressure	0.264	-	-	0.003	0.192E-05
Blood Cholesterol	0.181	-	-	0.762E-03	0.198E-05
Asthma	-	0.026	-0.039	-	-
Obesity	0.085	- 0.287	-	0.001	-
Heart Attack	0.045	-0.070	-	-	0. 662E-06