Built Environment, Travel, Nutrition and Health in Chinese Cities: Evidence from the China Health and Nutrition Survey

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Abstract

Using a longitudinal survey of households and communities in China, this study examines the potential causal relationship between the built environment and travel behavior, nutrition intake, and health of urban residents. The results support that: (1) household income, size, and accessibility to transit and schools affect motor vehicle ownership, though differently depending on motor vehicle type and city size; (2) increase in household income and ownership of motor vehicle reduce the likelihood of cycling or walking by adult commuters; (3) availability of fast food restaurants in neighborhood and ownership of car increase children's consumption of fast food; (4) the numbers of accessible supermarkets and free markets have opposite effects on urban residents' food consumption, measured by intakes of calorie, protein, carbohydrate and fat; and (5) adult body mass index is affected positively by income and negatively by education level and participation in housework. Overall, neighborhood food environment, such as access to markets and fast food restaurants, shows significant effects on urban residents' food and nutrition intake, but not significantly on their health outcomes. While some features of the built environment, such as accessibility to transit and schools, show little direct effect on travel behavior, nutrition intake, or health of Chinese urban residents. Nevertheless, evidence suggests that their effects may be indirect, through household vehicle ownership.

Keywords: People's Republic of China, Environment, Built environment, Travel, Transportation, Nutrition, Health, Chinese city, Urban

About the Author

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**Built Environment, Travel, Nutrition and Health in Chinese Cities:
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1. Urbanization, Motorization, and Health Challenges for China

Three decades of rapid economic growth not only significantly improved the material well-being of Chinese people, but also resulted in congestion, pollution, and chronic health problems such as obesity and diabetes, especially in China's cities. As the largest and fastest growing developing country, China's urban growth contributes to and faces threats from global climate change, energy shortage, and other fiscal and social problems.

According to the China Association of Automobile Manufactures, China became the largest market in the world for automobiles and trucks since late 2008, with more than a million autos and trucks sold each month since March 2009.[1] Even more startling is that the room of future growth in mobility seems enormous. The most recent data (Haddock & Jullens, 2009) show that China's overall auto usage was just 18 cars per thousand people in 2008, compared to 104 in Brazil and 213 in Russia. China, together with India, is probably producing an unprecedented wave of motorization, if its economy continues to grow. This trend is further assisted by the infrastructure-led economic development occurring in China. While the national expressway system only began operating in 1988, by the end of 2001, China's national expressway system became the second longest in the world.[2] By the end of 2008, total route length in operation exceeded 60,000 km, longer than the originally goal for 2010 (MOT, 2004). The construction of highways is still speeding up, due to the recent economic stimulus plan. Many suspect that the Chinese national expressway system will surpass the length of the U.S. Interstate System very soon. Unfortunately, the fast growth of these roads has already proven unable to match the pace of motorization. Peak hour speeds often drop below 15 or even 10 kilometers per hour in large cities. All these contributed to China's world-leading greenhouse gas emissions.

The urban environment and public health shoulder the consequences of China's income and urban growth. Numerous cities are on the list of the World Health Organization's most polluted cities in the world. According to Popkin (2008), China's number of overweight adult males/females tripled/doubled between 1989 and 2000, with nearly a quarter of all Chinese adults overweight by 2004. Moreover, the growth rate of Chinese overweight status, in particular among adults, is one of the highest in the world and far higher than that of the United States (Popkin, 2008). China has world's largest diabetes population, which is still growing rapidly. In addition, the urban landscape of food supply changes with the development of market economies. China is now experiencing the world's fastest growth in supermarkets (e.g. Carrefour, Wal-Mart and their domestic clones), with sales at these stores growing by as much as 40 percent annually (Hu et al., 2004). According to Hu et al, more than $55 billion had been spent on construction of supermarkets by 2003. These supermarkets are spreading to secondary cities and towns, and starting to reach higher-income populations in rural areas. It is common to

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[1] Data from http://www.caam.org.cn/, retrieved on Aug. 8, 2009.

[2] Data from http://www.jttj.gov.cn, retrieved on Aug. 8, 2009.

observe the replacement of free markets (also called fresh or wet markets) with supermarkets that supply more processed food, and the increase of fast food restaurants supplying Western and Chinese variants of pizza, hamburgers, fried chicken, etc., that tend to provide food and drinks with higher fat and sugar content.

Policies leading to greener and healthier cities in China are of global significance. All of the above aspects of urban development in China relate to urban land use and transport policies, which may in turn be expected to be employed by the government to reduce the negative environmental, energy and health consequences of growth. However, making effective and equitable policies is dependent upon a thorough understanding of the causal relationships between policy instruments (e.g. planning) and outcomes (e.g. travel behavior and health).

Through empirically examining the longitudinal data provided by the China Health and Nutrition Survey (CHNS), this study aims to advance a range of interconnected and increasingly overlapping literatures on the built environment, community resources, food environment, travel behavior, physical activity, and public health. In particular, it tries to seek evidence on the built environment and community resource's impact on urban residents' travel, exercise, and eating behaviors and health outcomes. Section 2 briefly reviews relevant literatures, emphasizing the merging of multidisciplinary perspectives, the need for more robust causal inference, and the lack of attention to the developing world. Section 3 describes the CHNS dataset. Section 4 presents the methodology used, including its limitations, followed by the results of analysis in Section 5. Section 6 summarizes the findings and discusses policy implications and limitations of this study.

2. Previous Studies

At least three interrelated literatures are relevant to this study. The two larger ones study relationships between the built environment and travel behavior and between the built environment and health. The relatively smaller literature is on effects of the accessibility to community resource, including studies on relationship between the food environment and nutrition intake.

The relationship between the built environment and travel behavior is an active research field by transportation and planning scholars primarily due to the interest in using a better planned built environment to reduce dependence on driving, traffic congestion, and related environmental and health impacts (e.g., climate change, energy shortage, air pollution, and lack of physical activity). There have been several reviews of this literature, such as Crane (2000), Ewing and Cervero (2001), Stead and Marshall (2001), Handy (2005), Guo and Chen (2007), Mokhtarian and Cao (2008), and Ewing and Cervero (2010). Most studies have shown that features of the built environment, such as the "three Ds" (density, diversity or land use mix, and design related to comfort, safety or interest) and street pattern (or connectivity), are often associated with travel behaviors including trip frequency, trip distance, mode choice, etc.

A closely linked literature, primarily by public health scholars, is on the relationship between the built environment and public health, mainly physical activity and chronic diseases (e.g. obesity).

There have also been several reviews of this literature, such as Frank and Engelke (2001), Humpel et al (2002), Kahn et al (2002), Trost et al (2002), Saelens et al (2003), Lee and Moudon (2004), Owen et al (2004), McCormack et al (2004), Krahnstoever-Davison and Lawson (2006), Heath et al (2006), Gebel et al (2007), Papas et al (2007), Saelens and Handy (2008), and Brownson et al (2009). Similar to the built environment—travel literature, most studies find physically active travel and health indicators such as body mass index (BMI) are correlated with the form of the built environment.

Different from the above literatures' focus on the physical form of the built environment, a smaller literature pays attention to *functional* aspects of the built environment (sometimes called community resources), such as the accessibility to transit or food. For example, Zheng (2008) and Edwards (2008) study the relationship between access to transit and health behaviors or health; Jeffrey et al (2006), Moore et al (2008), and Raja et al (2010) study the relationship between access to food and health behaviors or health; while Pearce et al (2006) expand the functional aspects to multiple types of community resources.

Unsurprisingly, the different strands of literatures are increasingly converging toward a common goal of understanding how the physical and functional aspects of the built environment affect human behavior and welfare at the community or city scale, as well as the global environment. For example, Frank et al. (2006) found that in usual American suburbs, an increase in neighborhood walkability is associated with more active travel time, fewer vehicle miles traveled (VMT), fewer emissions per capita, and fewer cases of obesity. Comprehensive literature reviews are increasingly paying attention to studies in multiple disciplines (see, e.g., Younger et al., 2008).

However, more and better empirical evidence is needed in order to advance our understanding of the effects of land use on travel and/or health for at least two reasons.

First, while a good number of studies have been conducted on urban land use, passenger travel and public health, the vast majority of existing evidence is based on cross-sectional data and only confirms the correlations between land use patterns and travel/health, leaving causality unexplained or falsely claimed, as in most studies reviewed in the meta-analysis of Brownson et al (2009) and Ewing and Cevero (2010).[3] Although a small number of studies, mainly by transportation/planning scholars, utilize a range of sophisticated statistical strategies to address the residential sorting and/or omitted variable biases (people's tendency to locate in areas consistent with their housing and travel preferences), most of their results are still suggestive (Guo & Chen, 2007, Mokhtarian & Cao, 2008) and do not seem to be very consistent with each other (TRB 2009, Guo 2009).

Larger and more complete longitudinal data are widely recognized to be crucial to address self-selection induced bias in estimating the built environment—travel—health relations (see, e.g. TRB 2005, 2009; Cao et al 2009). A small number of studies have utilized panel data, especially

[3] For example, individuals who favor a physically active lifestyle, a preference that is hard to measure correctly, might choose to live in neighborhoods facilitating such travel. Comparing such individuals with people living in communities with different built environmental features might overstate how the average person might respond to the differences in the built environment.

those of the movers and policy experiment. Using longitudinal changes of households that moved from the Puget Sound Transportation Panel, Krizek (2003) examines effects of changes in local accessibility on travel behavior.[4] In a natural-experimental study, Boarnet et al. (2005) surveyed parents of children to examine the impact of changes in the built environment on non-motorized travel by children affected by California's Safe Routes to School Program. Among the few studies using the adult longitudinal health data in the U.S. (the National Longitudinal Survey of Youth, 1979), Eid et al. (2008) have done a robust study utilizing the moves of young adults to detect the causal relationship between sprawl and obesity. However, the power of their evidence is limited by the fact that their data are essentially semi-longitudinal, because only land use changes of those who moved are accounted for (this may be acceptable for the U.S., but not for any rapidly urbanizing societies).

Second, almost all major empirical studies are from industrialized countries, where travel behavior, health background and the speed of land use change are completely different from those of developing countries, where air pollution and carbon emissions grow as rapidly as urbanization and motorization.[5] Data and analyses are very much needed to enrich our knowledge in the developing country setting, where on one hand, walking, cycling and transit use are much more important in comparison to the highly motorized Organization for Economic Co-operation and Development (OECD) countries, while on the other hand, significant and rapid socio-economic changes, including urbanization and motorization, in developing cities provide researchers with significant local built environment variations in time series data. In addition, cities in developing countries may experience the disappearing of free (or fresh, wet) market and surfacing of multinational and domestic large supermarkets, large providers of processed higher-fat, added-sugar, and salt-laden foods, and western fast food restaurants, helped by increased income and opportunity cost of time, refrigerators, globalization and trade, lower cost of transporting goods (Reardon et al., 2003). Also, the McDonald's, Pizza Huts, and Kentucky Fried Chicken restaurants are rapidly spreading across the globe. They are quickly followed, or even preceded, by local food chains that follow their models (Wang et al., 2002; Lobstein et al., 2004). However, very little research to date can provide analysis of the consequences of these food distribution shifts on dietary intake patterns. In the US, there is an increasing body of longitudinal research that appears to show how increased consumption of fast foods does link with obesity and diabetes, among others (Bowman et al., 2004; Pereira et al., 2005). But in developing countries, we are unclear whether they are leading people away from their healthy traditional diets to higher-fat and added sugar-laden prepared food.

Using the same dataset as used by this study, Bell et al (2002) confirm the correlation between motor-vehicle ownership and obesity in China. Zhang (2004) confirms the association between land use density and travel mode choice, controlling for travel time and monetary costs in Hong Kong. Also using the CHNS dataset, Van de Poel et al (2009) find that, in China, an aggregated measure of urbanization are associated with average risks of overweight and hypertension, controlling for individual demographics and socio-economic status. Cervero et al (2009) find that in Bogota, whereas road facility designs, like street density, connectivity, and proximity to Cicloviacutea lanes, are associated with physical activity, other attributes of the built

[4] However, Krizek acknowledged that no attempt was made to control for possible self-selection bias.

[5] A handful of exceptions include XXX.

environment, like density and land-use mixtures, are not. Zegras (2010) suggests that income dominates the household vehicle ownership decision, although there is also a correlations between several built environment characteristics and a household's likelihood of car ownership. In addition, this study also suggests a range of different design and relative location characteristics display a relatively strong association with VKT, but overall income plays the overall largest single role in determining VKT. Unfortunately, none of these studies were able to infer any true causality between the built environment and travel behavior and/or health, due to the potential self-selection bias.

3. Data

This study uses the China Health and Nutrition Survey (CHNS), a multi-wave ongoing longitudinal survey conducted jointly by the Carolina Population Center and China's Ministry of Public Health.[6] The CHNS currently consists of seven waves (1989, 1991, 1993, 1997, 2000, 2004 and 2006) with high follow-up rates (see Figure 1 and Table 1 for description of the CHNS dataset). It employs a multistage random cluster sampling process to draw households[7] from urban (and rural) areas in nine geographically and economically diverse provinces: Guangxi, Guizhou, Heilongjiang, Henan, Hubei, Hunan, Jiangsu, Liaoning, and Shandong. This dataset provides very detailed socio-economic, nutrition, and health information of households and individuals. In addition, it includes separate community questionnaire collecting information (e.g., accessibility) on community built environment or resources, such as transit, recreation facilities, public space, school/nursery, hospital, supermarket, fresh market, fast food chains, etc., at the neighborhood (*juweihui*) level.[8]

[6] Data supporting documentation and details on sampling are provided through the Carolina Population Center Web site (http://www.cpc.unc.edu/projects/china).

[7] Household member defined based on residency rather than official registration.

[8] A comprehensive review of the CHNS dataset can be found in Popkin et al (2009).

Figure 1. Participating Provinces (in dark green) of the CNHS

Table 1. Description of the Chinese Health and Nutrition Survey

	1989	1991	1993	1997	2000	2004	2006
Households	3795	3616	3441	3875	4403	~4400	~4400
Individuals	15917	14778	13893	14426	15648	~19000	~19000
Provinces	8	8	8	8	9	9	9
Urban neighborhoods	32	32	32	32	36	36	36
Town neighborhoods	32	32	32	32	36	36	36

The urban subsample of CHNS includes both larger cities in metropolitan areas and smaller urban places—towns where county-level non-agricultural activities agglomerate. A total 9,543 individuals from 2,473 households and 86 neighborhoods are identified in this multi-wave subsample. Average numbers of observed waves are 3.5 for individuals, 3.6 for households, and

5.3 for neighborhoods,[9] given the fact that Liaoning province was not surveyed in 1997, while Heilongjiang province was not survey prior to 1997. In the urban subsample, slightly less than half of the observations (46% of individuals and 49% of neighborhoods) are from prefecture-level cities, with the rest from county-level cities and towns. The neighborhoods vary in size of their areas, with a median of 1.1 km^2, a 25 percentile of 0.5 km^2, and a 75 percentile of 3 km^2. The population sizes of neighborhoods also vary, with a median of 2,400, a 25 percentile of 1,470, and a 75 percentile of 3,787.[10] Attrition (due to moving, death, etc.) is a relatively minor concern of the CHNS dataset. Although the CHNS survey only covers households and individuals remaining in the same neighborhood, the attrition rates of urban individuals are fairly low (6%) from 1989 to 1991 and relatively low during 1991–1993 (16%), 2000–2004 (18%) and 2004–2006 (17%). Only the periods of 1993–1997 and 1997–2000 have somewhat higher attrition (35% and 25%, respectively), primarily due to the changes of surveyed provinces in 1997.[11]

Compared to data used in existing literatures, the significant potential and advantage of the CHNS data can be summarized in three aspects. First, it offers true longitudinal data, with a significant number of household participants staying in the program for nearly two decades. Second, very few of the existing studies on the relationship between land use/built environment and travel/health use a random longitudinal dataset of comparable size. Most studies have sample sizes ranging from a few hundred to three to four thousands (see summaries by Papas et al. 2007 on the built environment and obesity, and Mokhtarian & Cao 2008 on the built environment and travel behavior). Third, the data offers very high quality income information on each individual, representing a significant advance in the measurement of income in China. Questions on income and time allocation probe for any possible activity each person might have engaged in during the previous year, both in and out of the formal market. Information on state-subsidized housing is gathered from respondents to generate in-kind income, so that full income from market and non-market activities is imputed, and is adjusted by provincial consumer price indexes.[12]

The CNHS dataset is large and complex. Missing data and likely mistakes or outliers have been identified to our best effort. To rule out potential outliers, analyses are restricted to urban

[9] In Mainland China, an urban neighborhood, also called (residential) community, is an urban residential area administrated by a subdistrict (in large cities, also called *Jiedao*), district (in medium sized cities), or city/town (in small cities/towns) government.

[10] One shortcoming of the CHNS dataset is that some variables are measured at neighborhood level, but urban neighborhoods vary in their sizes of area or population. According to the national laws regarding the establishment of urban neighborhoods, city or urban district governments designate neighborhood committees, each generally including 100 to 600 (old standard effective until 1989) or 700 (new standard effective since 1990) households.

[11] China's less developed housing market (gradual reform in urban housing market didn't start until early 1990s) and probably also less mobility in urban labor market can be explanations of the geographical stability of the sample.

[12] The annual earnings generally includes regular wages, other income from the work unit such as hardship allowance, Implicit rents associated with access to food and housing at below-market prices, private enterprise proprietor's pre-tax net income, individual enterprises proprietor's pre-tax net income, income of employees of individual enterprise, income of re-employed retired member, other employee income, second-job income, property income such as interest, dividends, net profits from stock/bond trading, property rentals, transfer income, and income from household sideline production. Household income can be negative if there is a loss in family business. For missing income sources, use imputation, mainly based on data from previous and following waves. So the CHNS survey provides better measures of urban subsidies and income from self-employment than in the National Bureau of Statistics (NBS) urban household surveys, the other major urban household surveys in China.

neighborhoods within 100 minutes (>99% of full urban household sample) of bicycling distance from nearest major medical facility, and within 25 km (96% of full urban household sample) from a park. Also, adults with weight heavier than 97.5 kg (and a few observations with obviously too low values), height lower than 74 cm, or BMI outside the 15–40 range, are excluded from analysis.

4. Methodology

The focus of this study is to analyze how neighborhood environment affects travel and health of Chinese urban residents. The causal effect of a change in neighborhood environment (treatment, T) on individual i is defined by $Y_{i,t0}^{T} - Y_{i,t0}$, which obviously is unobservable. With cross-sectional data we can estimate $Y_{i,t0}^{T} - Y_{j,t0}$, which provides the true causal effect only under the assumption that individuals i and j can be treated as the same, after controlling for their known differences. Unfortunately, this assumption is often too strong. The great advantage provided by longitudinal data is that we can run regressions using changes in both dependant and independent variables to cancel out unobserved individual characteristics that are constant overtime, which greatly controls the extent of unobserved heterogeneity.

Depending on the nature of the dependent variables (travel/eating behaviors or health outcomes), fixed-effect (FE) least squares or FE logit models are employed to estimate individual- or household-level average treatment effects using the panel data. In the case of FE logit, individuals with only 0s or 1s on the dependent variable are dropped because they provide no information for the likelihood. But the cost of this is often greatly reduced dataset size.[13] As a comparison, ordinary least square (OLS) and logit regressions using the pooled dataset are conducted to illustrate how different between focusing on the longitudinal dimension of the data and running naïve pooled regressions.[14] This helps us identify whether unobserved heterogeneity exists and affects the results. One limitation of the FE regressions, however, is that we cannot estimate the effects of time-constant covariates directly. One solution used here is to divide the sample into subsamples based on value of such covariates. For example, FE models are separately run for cities of different rank in the analysis of motor vehicle ownership. Another potential problem of the FE estimator is time-varying unobserved heterogeneity. The hope, however, is that most omitted variables are time-constant. Also, considering the limited attrition rate, selection bias is assumed to be minimal in this analysis.

The basic statistical model we will use to study built environment's impacts on travel, nutrition and health can be summarized as $\Delta y_{it} = \Delta x_{it}\beta + \Delta z_{it}\gamma + \Delta u_{it}$, with $t = 1, 2, \ldots, T$, where u_{it} is a time-varying household/individual error, and T represents the number of waves of survey data included in the regression.

[13] As one would expect, when the variation in independent variables is too few in terms of number of observations or too small in terms of magnitudes, we will have difficulty to estimate the FE regressions well – the standard errors will be too big. Also, measurement errors in independent variables may have also attenuated the effects.

[14] Still, compared with the cross-sectional regression the bias of the pooled data regressions would be lower, because pooled regressions also take into consideration of the within variation.

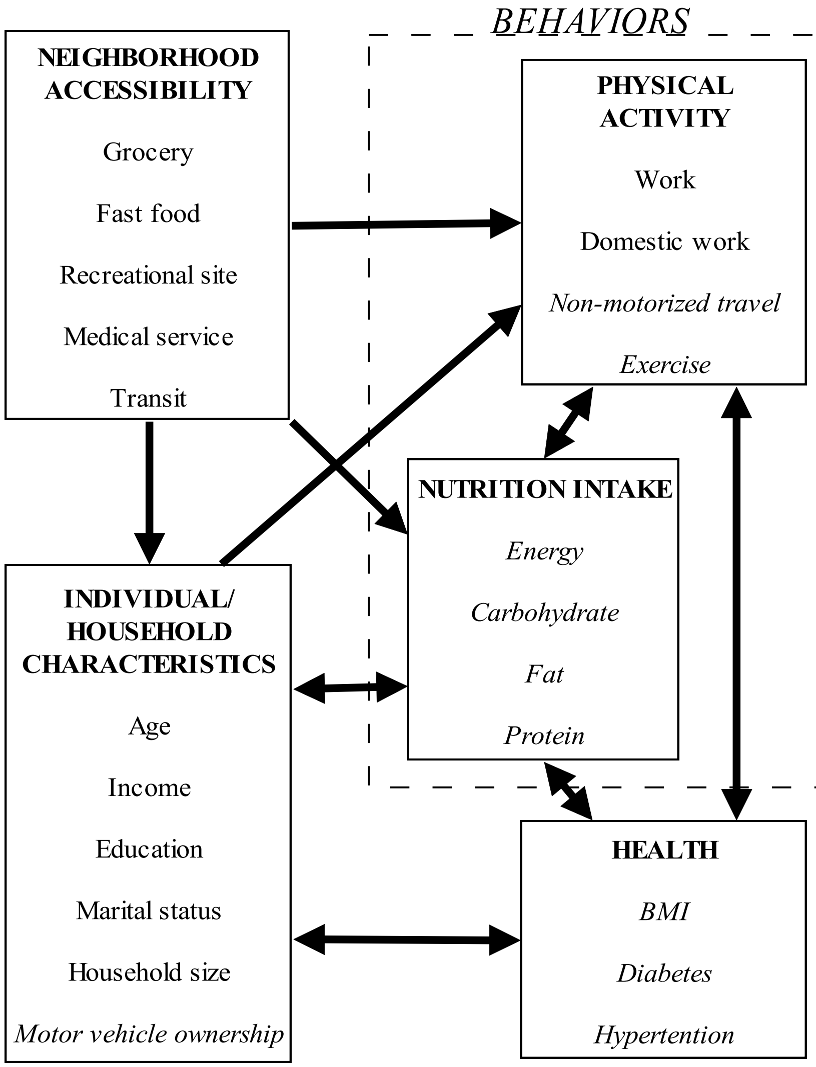
- y_{it} is the travel/eating behavior or health status of the household or individual i at time t, such as motor vehicle ownership, commute mode choice, physical activity, nutrition intake, BMI, and chronic diseases.

- x_{it} is a vector of observable individual/household characteristics. Household characteristics may include household inflation-adjusted full income, size, etc. Individual characteristics may include age, education, nature of occupation work (e.g. physical intensity), etc.

- z_{it} is a vector of built environment variables of the household's neighborhood. z_{it} can include each household's accessibility to most major destinations such as schools, health services, markets (supermarkets and free/wet markets), fast food restaurants, recreation sites, and bus stops.[15]

[15] Admittedly, built environment features such as land use density or urban design characteristics (e.g. street connectivity and availability of sidewalk) are missing in this dataset.

Figure 2. Diagram Relating the Built Environment to Physical Activity, Nutrition, and Health



The rationale of selecting independent variables in different regressions is illustrated in Figure 2, which shows the schematic relationship among the major variables analyzed in this study. Our major assumption is the exogeneity of the built environment/neighborhood resource to household/individual behaviors and health outcomes. Table 2 provides a description of the variables.

Table 2. Description of Variables

Variable	Description
Household characteristics	
Income	Net household income inflated to 2006 provincial price

Size	Number of household member
Car ownership	Dummy variable: a household possess one or more cars (=1), otherwise (=0)
Motorcycle ownership	Dummy variable: a household possess one or more motorcycles (=1), otherwise (=0)
Individual characteristics	
Age	Age in years at time of survey
Education	Years of formal education
Married	Dummy variable: married (=1) or unmarried/divorced/widowed (=0)
Occupational activity level	Physical intensity of work: 1=very light (working in a sitting position; 2=light (working in standing position); 3=moderate (student, driver, electrician, metal worker, etc.); 4=heavy (farmer, dancer, steel worker, athlete, etc.); 5=very heavy (loader, logger, miner, stonecutter, etc.)
Physical exercise participation	Dummy variable: adult (>18 yrs) participation in physical exercise (=1), otherwise (=0)
Housework participation	Dummy variable: adult (>18 yrs) participation in domestic housework (food shopping, cooking, laundry, cleaning or child caring) (=1), otherwise (=0)
Built environment	
Bus in neighborhood	Dummy variable: neighborhood has bus stop (=1), otherwise (=0)
School in neighborhood	Number of levels of public schools (primary, lower-middle and high-middle) in neighborhood
No. of supermarkets in 5km	Number of super/hypermarkets in 5 km of neighborhood
No. of free markets in 5km	Number of free/fresh/wet markets in 5 km of neighborhood
Distance to park	Distance (km) from nearest park or entertainment center
Distance to playground	Distances to nearest recreation site/facility and public space
Fast food in neighborhood	Dummy variable: neighborhood has foreign fast food restaurant(s) (=1), otherwise (=0)
No. of fast food	Number of foreign fast food restaurants in neighborhood

restaurants	
Distance to medical facility	Distance (in minutes by bicycle) to major health service providers to household
Travel behavior	
Commute by motor vehicle	Dummy variable: commute by car or motorcycle (=1), otherwise (=0)
Commute by bicycle or foot	Dummy variable: commute by bicycle or foot (=1), otherwise (=0)
Commute by transit	Dummy variable: commute by bus or rail (=1), otherwise (=0)
Eating behavior	
Fast food consumption	Foreign fast food store visits in past 3 months by children (6–18 yrs)
Calorie intake	3 day-average calorie intake (kcal)
Protein intake	3 day-average protein intake (g)
Carbohydrate intake	3 day-average carbohydrate intake (g)
Fat intake	3 day-average fat intake (g)
Health outcome	
BMI	Measured body mass index
Hypertension	Dummy variable: diagnosed with high blood pressure (=1), otherwise (=0) (self-reported by interviewees older than 12 yrs)
Diabetes	Dummy variable: diagnosed with diabetes (=1), otherwise (=0) (self-reported by interviewees older than 12 yrs)

5. Does the Built Environment Matter?

5.1 Travel Behaviors and Motor Vehicle Ownership

Table 3 presents logit models individual, household and neighborhood characteristics to adult commuters' choice of non-motorized mode. The logit analysis of pooled panel data (Model 1) presents a list of correlations between non-motorized commute and age (non-motorized travel increases up to around age 40 and then decreases), education (non-motorized travel decreases as education level increases), motor vehicle ownership (negative relationship), transit service (negative relationship),[16] and domestic work participation—an indicator of burden of physical activity other than commute (positive relationship). The complementary instead of substitute relationship between participation in domestic work and active commute may indicate unobserved heterogeneity of adult individuals such as physical capacity.

Table 3. Determinants of Adult Commute Mode: Non-Motorized

	Model 1	Model 2	Model 3	Model 4	Model 5
	Pooled logit	FE logit	FE logit	FE logit	FE logit
Household income	-0.0000027	-0.00000249	-0.0000112**	-1.19E-06	-0.00000902**
Age	0.0820652***	5.163721	2.003383	3.601969	0.1851019
Age^2	-0.0010294***	-0.0037344	-0.0005991	0.0000875	0.0019355
Education	-0.0398076**	-0.5625105*	0.076416	-0.4068771*	0.0038956
Owning motorcycle	-1.105978***	- 2.289811***	-1.518575***		
Owning car	-0.5599596**	-0.6306271	-0.1461853		
Bus in neighborhood	-0.1697159	-0.0707481	-0.1299474		
Occupational activity level	0.0997583	-0.1090203		-0.0671612	
Physical exercise	0.1255967	-0.1113662		0.2244058	
housework	0.1698528***	0.1737615		0.0685174	
Sample size	*1947*	*230*	*436*	*238*	*460*
Pseudo R^2	*0.0663*				
Prob>chi^2	*.0000*	*.0024*	*.0001*	*.2747*	*.0439*

[16] Transit here only refers to bus but not rail. For all neighborhoods in the sample period, there was no rail service available.

Household motor vehicle ownership seems negatively affect adult active commute, with the effect of motorcycle ownership more significant than car ownership, probably due to the much fewer positive observations of the latter. The availability of bus service in neighborhood, though negatively correlated with adult active commute, fails to show statistically significance in the FE models. The negative effect of household income level on adult active commute is statistically significant in models with larger samples (Models 3 and 5), while adult individuals' other physical activities are not controlled for. The negative effect of age on adult active commute is only statistically significant in the largest sample (among FE models) and most reduced form of regression (Model 5). The negative effect of education on adult active commute is statistically significant in models with smaller samples, while adult individuals' other physical activities are controlled for. Work, home, and recreational physical activities, though showing positive correlations with active commute (only statistically significantly so for housework), show mixed signs in the FE models and are insignificant.

To sum, motor vehicle ownership shows important impact on adult commuters' choice of non-motorized modes, supported by the difference in chi^2 values between Models 3 and 4. Income and education, though correlated with active commute, have inconsistent effects across FE model specifications. FE models also reject that there are statistically significant causal relationship between active commute and bus service or domestic work, as indicated by the pooled sample regression in Model 1.

Using the same model specifications, Table 4 presents results from logit regressions of adult commuters' choice of public transit. Although age, education, motorcycle ownership, bus service, and occupational activity level are correlated with commuting by transit, FE models of different specifications and sample sizes are unable to confirm any of the factors' causal relationship with transit commute.

Similarly, Table 5 presents results on adult commuters' choice of individual motorized modes (car, motorcycle or taxi). Again, although income, age, education, motor vehicle ownership, and participation in domestic work are all correlated with commuting by individual motorized modes, the only statistically significant factor confirmed by the FE models is the ownership of motor vehicles.

Table 4. Determinants of Adult Commute Mode: Transit

	Model 1	Model 2	Model 3	Model 4	Model 5
	Pooled logit	FE logit	FE logit	FE logit	FE logit
Household income	0.00000131	-6.64E-06		-7.45E-06	4.51E-06
Age	-0.1082471***	-7.369542		-6.932674	-1.78562
Age^2	0.001112**	0.01119		0.012355	0.005796
Education	0.2066597***	0.274299		0.303481	0.03408

Owning motorcycle	-0.9470493***	-0.317295			
Owning car	-0.4294195	-1.168971			
Bus in neighborhood	0.5619786***	-0.258602			
Occupational activity level	-0.2606519***	0.257015		0.310569	
Physical exercise	0.0921385	0.646541		0.585734	
housework	0.0206176	-0.01296		0.010127	
Sample size	*1946*	*122*	*230*	*122*	*238*
Pseudo R^2	*.1157*				
Prob>chi^2	*.0000*	*.4488*		*.2523*	*.5660*

Table 5. Determinants of Adult Commute Mode: Individual Motorized

	Model 1	Model 2	Model 3	Model 4	Model 5
	Logit	FE logit	FE logit	FE logit	FE logit
Household income	0.00000407*	0.00000716	0.00000606	9.35E-06	5.86E-06
Age	0.1871579***	-5.886144	-1.964312	-3.231921	-0.167579
Age^2	-0.0024665***	-0.0013479	0.000735	-0.01015	-0.002838
Education	0.0857529***	-0.2997917	-0.193927	-0.240028	-0.076617
Owning motorcycle	2.476229***	3.284908***	1.967082***		
Owning car	1.127953***	2.518091**	1.278143*		
Bus in neighborhood	0.1343712	-0.9244117	-0.1794215		
Occupational activity level	-0.0152965	-0.4641893		-0.210795	
Physical exercise	-0.1210175	-0.1426003		-0.463073	
housework	-0.3640157***	0.0296669		0.098897	

Sample size	*1947*	*130*	*252*	*132*	*260*
Pseudo R2	*.2458*				
Prob>chi2	*.0000*	*.0026*	*.0000*	*.6954*	*.3100*

Overall, results from Tables 3 to 5 fail to confirm the causal relationship between mode choice of adult commuters and income, age, education, bus service, major non-commute physical activities. The only significant driven force of more individual motorized or fewer active commute trips seems to be the ownership of motor vehicles, which is in turn the result of different factors. Tables 6 and 7 contain the result of further investigations on the determinants of household ownership of car and motorcycle.

In Table 6, household car ownership is correlated with household income, size, accessibility to schools and free markets, as shown in the logit analysis of the pooled panel in Model 1.[17] In the FE logit Model 2, only household size shows statistically significant positive effect on car ownership, but the overall model suffers from its sample size—too few households changed (i.e. gained) car ownership in the data set. Model 3 thus uses a further reduced form, but regressions are conducted over the full sample, households of prefecture-level cities and county-level cities (towns). Income shows positive impact on household car ownership in both the full sample and the prefecture-level cities. Household size positively affects car ownership only in county-level cities/towns.[18] The availability of bus service in neighborhood, while reduces car ownership in county-level cities/towns, raises the likelihood of household car ownership in prefecture-level cities. In prefecture cities, the effect of bus service availability roughly equals the effect from a rise of 67,000 RMB of household income. In county-level cities, the effect of bus service availability, however, cancels out an increase of about two members in household size. The difference in driven force of household car ownership between the prefecture- (usually larger) and county- (usually smaller) level cities is interesting. It suggests that car ownership is more driven by income/affordability and cannot be substituted by bus service in larger cities (the positive effect of bus service might indicate the level of urbanization or community service/amenity), while in smaller cities, car ownership is more driven by cost-effectiveness (bigger households can take more advantage of household car ownership and share the cost) and can be substituted by bus service.

Table 7 shows that in addition to household income, size and associability to schools and free markets, distance to playground is also correlated with household motorcycle ownership, as shown in Model 1. However, the corresponding FE logit Model 2 only confirms the positive effect of household size. Model 3 drops accessibility measures to markets and recreational sites to include more observations. FE logit analysis of the full sample shows that household size and bus service positively affects motorcycle ownership, while more accessible schools reduces the likelihood of owning motorcycles. Disaggregating the sample into prefecture- and county-level

[17] Due to data availability of accessibilities to markets and recreational sites, sample size is reduced in regressions with those variables.

[18] As one may expect, household size is more variable in county-level cities, which have a standard deviation of 1.49 vs. 1.26 in prefecture-level cities.

cities, one can find that higher household income negatively affects motorcycle ownership in larger cities, and larger households are more likely to own motorcycles in both subsamples. Both availability of bus service and accessibility to schools show similar effects on motorcycle ownership in the two subsamples, but lack the statistical significance obtained in the full sample regression. Results of both Tables 6 and 7 indicate that neighborhood access to bus may have different meanings in cities of different sizes.

Table 6. Determinants of Household Car Ownership

	Model 1	Model 2	Model 3		
	Pooled logit	FE logit	FE logit Full sample	FE logit Prefecture	FE logit County
Household income	0.0000118***	-1.71E-05	0.00000424	0.0000147**	0.000000237
Household size	0.3802677***	1.091963*	0.3864832***	0.1341221	0.4868885***
Bus in neighborhood	-0.0046895	-2.140421	-0.1724528	1.027984*	-0.7876257**
School in neighborhood	-0.3636841***	0.54562	-0.0376311	0.071175	-0.0836948
No. of supermarkets in 5km	-0.008513	0.10782			
No. of free markets in 5km	-0.1198249**	-0.158799			
Distance to park	0.0028151	1.397445			
Distance to playground	0.0345226	-0.081396			
Sample size	*2042*	*48*	*461*	*171*	*290*
Pseudo R^2	*.1086*				
Prob>chi^2	*.0000*	*.3013*	*.0001*	*.0268*	*.0001*

Table 7. Determinants of Household Motorcycle Ownership

	Model 1	Model 2	Model 3		
	Pooled logit	FE logit	FE logit Full sample	FE logit Prefecture	FE logit County
Household income	0.00000558***	-0.0000157	-0.00000284	-0.0000097*	-0.000000845
Household size	0.6740391***	1.254875***	0.8499568***	0.8619904***	0.8955934***
Bus in neighborhood	0.1364281	-0.3518774	0.746156***	0.8550652	0.8006069**
School in neighborhood	-0.131407**	0.3775867	-0.1474691	-0.1666563	-0.0646917
No. of supermarkets in 5km	-0.0072926	0.0550378			
No. of free markets in 5km	-0.0139751*	0.0235992			
Distance to park	0.0094879	-0.1115394			
Distance to playground	0.0458806**	-0.1354506			
Sample size	*2044*	*154*	*588*	*282*	*306*
Pseudo R^2	*.1167*				
Prob>chi^2	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*

5.2 Food and Nutrition Intake

Table 8 presents regression results on how various individual, household and built environment factors affect fast food consumption by children in urban households. Model 1's OLS regression of the pooled sample shows that household income, availability of fast food in neighborhood are positively associated with children's patronage of fast food restaurants. An unexpected correlation is between the number of free markets within in five km of the neighborhood and children's fast food consumption. However, the magnitude of such a positive correlation seems to be quite limited. The FE model (Model 2) obtains different result, rejecting that the correlations in the OLS regression represent causal relationship. It shows a significant positive effect of the number of fast food restaurants on children's fast food consumption—one more fast food restaurant around the neighborhood on average will increase a child's visit times to fast food restaurants by close to 0.6 times during a three-month period. Also, quite interestingly, independent of household income, household car ownership significantly boosts children's visits to fast food restaurants. Relative to children in households without cars, children in households with cars pay about 3.6 additional visits to fast food restaurants. Given that the effect of the availability of fast food restaurant within neighborhood is quite small and insignificant statistically, one may conclude that in addition to the local food environment, household mobility significantly increases the access to fast food by children.

Tables 9 to 12 report regression results of adults' intake of calorie, carbohydrate, protein and fat[19] from food, taking into consideration individual (age, education and occupational activity level) and household (income, vehicle ownership and distance to medical facilities) characteristics and neighborhood food environment. A group of OLS and FE models with identical specifications are used in each of the tables.

Table 9 reports how the most aggregate measure of nutrition—calorie—is associated or affected by various factors. The OLS models (Models 1, 3 and 5) generally find that calorie intake is positively associated with age (at a decreasing speed), occupational activity level, and number of free markets around neighborhood, while negatively associated with availability of bus service, number of supermarkets around neighborhood and the availability of fast food restaurants in neighborhood. Mixed findings are found for the effects of education (insignificant when sample size enlarged), household income (shifting from positive to negative effect when sample expands), and motor vehicle ownership (shifting from positive to negative when sample expands). The FE models (Models 2, 4 and 6), however, portray a quite different picture that should probably tell us more about the causal effects. The FE models confirm the OLS results that higher occupational activity levels lead to more calorie consumption, but with a reduced magnitude (56 in Model 6 vs. 109 in Model 5). They also confirm the OLS results that more supermarkets around leads to less calorie intake, while more free markets around leads to more calorie intake, both with larger magnitudes. The FE models also disagree with the OLS results in many ways. As people grow older, their calorie intake decreases (at a decreasing rate). Household income seems to have a positive but minimal effect on calorie intake. The results on motor vehicle ownership and bus service availability are mixed and unclear.

The results on carbohydrate, shown in Table 10, are quite similar to those on calorie. The only major difference here is that although OLS models find mixed results about how carbohydrate intake associates with availability of fast food in neighborhood, the FE models (Models 2 and 4) seem to suggest that neighborhood fast food availability increases adult intake of carbohydrate. The results on protein intake (Table 11) show two differences compared to those on calorie: higher education level and motorcycle ownership lead to more protein intake. The results on fat intake (Table 12) deviate from those on calorie a little further. The effect of age is less clear.

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[19] Obviously, the different types of nutrition are often taken together, with high correlations (coefficient>0.8) between calorie and carbohydrate, and between calorie and protein, and significant correlations (coefficient>0.5) between calorie and fat, carbohydrate and protein, and between fat and protein. The only week correlation is between carbohydrate and fat intakes (coefficient is about 0.2).

Occupational activity level on adult fat intake is unclear, if not negative. But the result that is consistent across all four nutrition intake analyses maintains—higher number of supermarkets around reduces intake, while higher number of free markets around increases intake.

Table 8. Determinants of Fast Food Consumption by Children

	Model 1	Model 2
	OLS	FE
Household income	0.0000171***	-0.0000184
Age	-0.0317358	2.24385
Owning car	0.5822357	3.658265**
Bus in neighborhood	-0.2312126	-0.5579227
Fast food in neighborhood	0.3784657*	0.1286976
No. of fast food restaurants	0.0080729	0.5612374***
No. of supermarkets in 5km	-0.0031714	-0.0121796
No. of free markets in 5km	0.0479118**	-0.043796
Distance to medical facility	0.0170843	-0.055143
Sample size	*527*	*527*
Adj./within R^2	*.0441*	*.1727*
Prob>F	*.0002*	*.0303*

Table 9. Determinants of Adult Nutrition Intake: Kilocalorie

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OLS	FE	OLS	FE	OLS	FE
Age	28.07036***	577.4271**	27.65017***	443.705*	18.43863***	552.8088***
Age^2	-0.2991764***	-0.2342266	-0.2982087***	-0.2095516	-0.2280162***	-0.0417966
Education	11.62275***	-2.517009	10.9219***	-0.3759719	7.896724***	1.496491
Occupational activity level	84.87873***	21.95652	88.3575***	22.53251	95.99347***	46.75894***
Household income	0.0010333***	0.0000825	0.0012455***	0.0000208	0.0001894	0.0011256***
Owning car	82.84824*	24.76808			43.07427	-29.15343
Owning motorcycle	59.10434***	123.6991**			0.032978	15.53786
Bus in neighborhood	-2.298707	108.5637***			-18.37029	2.285222
Distance to medical facility	-1.030821	0.7190839	-1.139647	0.4009854		
No. of supermarkets in 5km	-8.307769***	-13.55629***	-8.125207***	-12.41356***		
No. of free markets	6.750866***	17.67285***	6.497348***	17.64373***		

in 5km						
Fast food in neighborhood	-124.7904***	52.87673	-123.8747***	71.57573**		
Sample size	*5305*	*5305*	*5313*	*5313*	*16389*	*16389*
Adj./within R^2	*.0749*	*.0669*	*.0738*	*.0594*	*.1068*	*.0781*
Prob>F	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*

Table 10. Determinants of Adult Nutrition Intake: Carbohydrate

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OLS	FE	OLS	FE	OLS	FE
Age	3.682042***	103.9136***	3.628114***	89.01875**	1.810093***	83.10439***
Age^2	-0.0406495***	-0.0962893*	-0.0406024***	-0.0936248*	-0.0277498***	0.0046317
Education	0.4784925	-0.4094257	0.3813732	0.0204223	-0.773338***	0.6129427
Occupational activity level	21.7778***	10.69134***	22.47802***	11.3037***	23.49647***	10.5571***
Household income	-0.0000141	0.0000448	0.000000554	0.0000301	-0.0001976***	0.0000477
Owning car	-0.4792163	0.3379982			1.252311	-5.017939
Owning	10.16099***	31.721***			-4.927152**	0.2022204

motorcycle						
Bus in neighborhood	3.603821	13.5745**			-5.048886***	0.0499903
Distance to medical facility	-0.4498944***	0.2461652	-0.4697358***	0.1698412		
No. of supermarkets in 5km	-1.092556***	-0.8792083**	-1.038958***	-0.7033846*		
No. of free markets in 5km	-0.0219737	1.672517***	-0.0404973	1.676084***		
Fast food in neighborhood	-18.04665***	13.16148**	-17.59832***	15.80072***		
Sample size	*5302*	*5302*	*5310*	*5310*	*16370*	*16370*
Adj./within R^2	*.0937*	*.0625*	*.0927*	*.0484*	*.1815*	*.1341*
Prob>F	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*

Table 11. Determinants of Adult Nutrition Intake: Protein

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OLS	FE	OLS	FE	OLS	FE
Age	0.7978557***	31.65377***	0.7703932***	24.72206***	0.6049534***	19.92882***
Age^2	-0.0085861***	-0.0046309	-0.0084812***	-0.003128	-0.006837***	-0.0030031*
Education	0.7270977***	0.2869745	0.6963938***	0.3929427	0.6578494***	0.4336904**
Occupational activity level	1.214144***	1.288304*	1.391119***	1.310322*	1.954968***	1.254106***
Household income	0.0000858***	0.0000294	0.0000966***	0.0000257	0.0000651***	0.0000655***
Owning car	1.393353	-0.7508671			0.3900484	-1.517999
Owning motorcycle	4.753653***	5.985366***			3.677853***	1.812886**
Bus in neighborhood	-3.360475***	5.714754***			-1.896989***	-1.30211**
Distance to medical facility	0.0599885	0.0605921	0.0405848	0.0479259		
No. of supermarkets	-0.0535523	-0.4661659***	-0.0587463	-0.404645***		

in 5km						
No. of free markets in 5km	0.1988819***	0.4477617***	0.1727571***	0.4496273***		
Fast food in neighborhood	-2.633782***	-0.3277763	-2.82009***	0.7705417		
Sample size	*5297*	*5297*	*5305*	*5305*	*16364*	*16364*
Adj./within R^2	*.0759*	*.0521*	*.0673*	*.0370*	*.0659*	*.0302*
Prob>F	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*

Table 12. Determinants of Adult Nutrition Intake: Fat

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
	OLS	FE	OLS	FE	OLS	FE
Age	0.7993366***	3.011157	0.794264***	-3.074545	0.7949656***	10.48235**
Age^2	-0.0086198***	0.0167502	-0.0085591***	0.0173119	-0.0084989***	-0.0028805
Education	0.5695734***	-0.1970748	0.567499***	-0.1806308	0.8044284***	-0.1222237
Occupational activity level	-1.159812*	-2.926363**	-1.197928*	-3.055132**	-1.575197***	-0.3444665
Household	0.0000809***	-0.0000135	0.0000875***	-0.0000123	0.00008***	0.0000595***

income						
Owning car	5.445089**	4.723349			2.416074	-1.99475
Owning motorcycle	-0.7730476	-1.093356			-0.9392969	-0.3829061
Bus in neighborhood	-0.4792925	4.874957**			0.9820503	1.259775
Distance to medical facility	0.0731269	-0.0421271	0.0772852	-0.0389654		
No. of supermarkets in 5km	-0.4259236***	-0.7603484***	-0.4288588***	-0.7154086***		
No. of free markets in 5km	0.582327***	0.8515326***	0.5822152***	0.8424565***		
Fast food in neighborhood	-3.675752***	-0.9842427	-3.766488***	-0.3152522		
Sample size	*5291*	*5291*	*5299*	*5299*	*16283*	*16283*
Adj./within R^2	*.0349*	*.0427*	*.0346*	*.0406*	*.0319*	*.0161*
Prob>F	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*	*.0000*

5.3 Physical Exercise

Table 13 presents results from logit regressions of adult participation in physical exercise. Results of pooled logit regressions (Models 1, 2, 4 and 6) suggest that education, income, and bus service are positively correlated with the likelihood of adult participation in physical exercise, while occupational activity level and participation in domestic work are negatively correlated with the likelihood of adult participation in physical exercise. Participation in physical exercise decreases with age initially but increases later. The FE models (Models 3, 5 and 7) only confirm that education and bus service increase adult participation in physical exercise, but fail to find statistical significant effect of accessibility to parks or playgrounds. They were also unable to test other whether physical activities—active commute and participation in domestic work—affect adult participation in exercise due to insufficient observations.

5.4 Health Outcomes

Three health outcomes, measured[20] BMI (obtained by dividing a person's weight in kilograms by the square of height in meters is used[21]), stated history of diabetes, and stated history of hypertension, are studied for adult between 20 and 75 years old.[22] Tables 14 to 16 present regression results on the relationship between each of the three adult health outcomes—BMI, hypertension and diabetes—and individual, household, and neighborhood characteristics.

In Table 14, eight models are specified to evaluate the relationship between adult BMI and (1) individual and household characteristics, (2) distances to recreational and medical facilities, (3) vehicle ownership and bus service, and (4) availabilities of fast food and markets, together and separately. OLS estimates (Models 1, 3, 5 and 7) suggest that adult BMI increases with age (up until mid 60s) and motorcycle ownership but decreases with education, participation in housework, distance to medical facility and availability of bus service. No association is found between BMI and household income level, occupational activity level, and distances to recreational sites. The relationship between BMI and fast food restaurants and markets is also unclear (negative relationships found in Model 5 but not Model 1, when transportation means are controlled for).

The FE results are different. In particular, none of the coefficients on neighborhood environment/resource (e.g., distances to facilities and availabilities of food and markets) is statistically significant. More education is confirmed to lower adult BMI, with one additional year education lowering BMI by 0.08 to 0.21. Participation in housework also seems to lower adult BMI by 0.12 to 0.15, especially when neighborhood environment is controlled for (Models 2, 4 and 6). Household ownership of motorcycle might increase adult BMI, but only when neighborhood environment is not controlled for (Model 8). Age's effect on BMI seems to confirm the OLS results, but not quite robustly. Household income also seems to have a fairly small positive effect on BMI, but not that robustly either.

[20] In most studies of BMI, data on height and weight are collected based on self-reports, which can often be different from survey results based on physical examination. Such bias is avoided in the CHNS dataset.

[21] Overweight is defined as a BMI higher than 25 but less than 30, and obesity as a BMI higher than 30.

[22] Compared to adults, hypertension and diabetes of children are often due to genetic rather than lifestyle reasons. The CHNS only collects hypertension and diabetes information from people of 12 years or above.

Using logit regressions with similar specifications as in Table 14, Tables 15 and 26 reports how adult incidences of hypertension and diabetes are related or affected by the independent variables. In general, neighborhood environment does not seem to significantly affect the likelihood of adult hypertension or diabetes, the only exception being the local markets and diabetes. FE results in Table 16's Models 5 and 6 suggest that more supermarkets around might increase the incidence of adult diabetes, while more free markets around might reduce the likelihood. There are also little consistent FE model results on individual and household characteristics' effects on adult hypertension or diabetes.

Table 13. Determinants of Adult Participation in Physical Exercise

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Pooled logit	Pooled logit	FE logit	Pooled logit	FE logit	Pooled logit	FE logit
Age	-0.1575904***	-0.0842392***	-3.143745*	-0.067979***	-3.033088***	-0.069398***	-3.243452***
Age^2	0.0018093***	0.0008662***	-0.001592	0.000724***	-0.0006339	0.0007331***	-0.0005664
Household income	0.0000012	0.00000258**	7.03E-06	0.00000267**	0.00000147	0.00000246**	0.00000142
Occupational activity level	-0.026842	-0.0481236	-0.035549	-0.0850194**	0.0137112	-0.0909013***	0.0001596
Owning car	-0.0835911			-0.4317391**	-0.1228941		
Owning motorcycle	-0.0265972			0.1404991**	-0.0890725		
Bus in neighborhood	0.4079014**			0.1422267**	0.1641341		
Distance to medical facility	-0.003632	0.0058585	0.0036586	0.0046137	-0.0027391	0.0045908	-0.0031506
Education	0.1541073***	0.1148294***	0.0773616	0.1148011***	0.0898168**	0.1153106***	0.0931665**
Active commute	0.0465014						

Housework	-0.1260852**						
Distance to park	-0.000184	-0.0030522	0.0399815				
Distance to playground	0.0467112**	0.0256068**	0.0766118				
Sample size	*1506*	*4273*	*512*	*9025*	*2466*	*9277*	*2587*
Pseudo R^2	*.0592*	*.0434*		*.0420*		*.0409*	
Prob>chi^2	*.0000*	*.0000*	*.0876*	*.0000*	*.0000*	*.0000*	*.0000*

Table 14. Determinants of Adult BMI

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Age	0.2058554***	0.5346301	0.1986037***	-0.7724112	0.1932401***	-0.1622928	0.1946486***	0.8464817
Age^2	-0.0015434***	-0.0016066	-0.0014804***	-0.0003998	-0.0015027***	-0.0007411	-0.0014969***	-0.0014683**
Household income	0.00000157	0.00000545*	0.00000339	0.00000453	0.00000215	0.00000201	0.000000794	0.0000012
Education	-0.040945**	-0.2066533***	-0.0436402**	-0.1643668***	-0.0551784***	-0.0946777**	-0.0422564***	-0.0727996**
Married	0.1911118	0.4530344	0.280672	0.5924252	0.604738**	0.5511501	0.5733004**	0.4148429
Occupational activity level	0.057619	-0.0946936	0.0500013	-0.0577951	0.0095865	-0.0327408	-0.0136272	0.023385

Housework	-0.0942537*	-0.148641**	-0.0973702*	-0.1206187**	-0.1273211***	-0.1232213**	-0.0737696*	-0.0140701
Distance to medical facility	-0.0111229	0.0038479	-0.0143034**	-0.0006334				
Distance to park	0.0169924	-0.0152817	0.0197159	-0.0021667				
Distance to playground	0.0096237	0.0036276	0.010901	-0.0083981				
Owning car	0.4383846	-0.1437441					0.3470649	-0.2835603
Owning motorcycle	0.308734**	0.3172447					0.313097**	0.2078605
Bus in neighborhood	-0.6488325***	0.1363807					-0.4398648***	-0.007079
No. of fast food restaurants	-0.0265672	-0.0377779			-0.0443393**	-0.0200035		
No. of supermarkets in 5km	-0.0209915	0.0169649			-0.0041748	0.0024882		
No. of free markets in 5km	-0.0127503	0.0119727			-0.0173695*	0.0082004		
Sample size	*2791*	*2791*	*2891*	*2891*	*3661*	*3661*	*4221*	*4221*

Adj./within R^2	*.0702*	*.0693*	*.0618*	*.0490*	*.0596*	*.0192*	*.0644*	*.0312*
Prob>F	*.0000*	*.0012*	*.0000*	*.0010*	*.0000*	*.0470*	*.0000*	*.0000*

Table 15. Determinants of Adult Hypertension

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
	Pooled logit	Pooled logit	FE logit	Pooled logit	FE logit	Pooled logit	FE logit
Age	0.1887314***	0.1964352***	4.278693	0.2293755***	4.22132	0.2355371***	2.688258
Age^2	-0.0009697*	-0.0010289**	0.0037271	-0.0013487***	0.0027279	-0.0013946***	0.0005625
Household income	0.00000217	0.00000305	0.0000293*	0.0000025	9.13E-06	0.00000147	0.00000481
Education	0.0026818	0.005012	-0.0979009	-0.0045856	-0.06314	0.0031204	-0.1671311*
Married	1.060616	1.060114	14.49907	0.9095909	14.52715	0.5459978	-0.3466271
Occupational activity level	-0.2068598**	-0.2043949**	-0.4744897	-0.0883769	0.0499495	-0.1442854**	-0.0679705
Housework	-0.0528459	-0.0462327	0.4897877	-0.0420382	-0.004096	-0.0206369	0.0702074
Distance to medical facility	0.0093641	0.0086951	-0.0054991				
Distance to park	-0.0034585	-0.0055148	-0.0616111				

Distance to playground	0.055274***	0.0518932***	-0.008585				
Owning car	0.674114**					0.3942466	0.1625816
Owning motorcycle	-0.0772496					0.1110357	-0.2330314
Bus in neighborhood	-0.2965746**					-0.2072188*	0.0426424
No. of fast food restaurants	-0.0045265			-0.0321104	-0.080652		
No. of supermarkets in 5km	0.0141909			0.0190656*	0.0470451		
No. of free markets in 5km	0.0001418			-0.0027112	-0.05463		
Sample size	*2979*	*3091*	*120*	*3903*	*214*	*4517*	*320*
Pseudo R^2	*.1619*	*.1586*		*.1462*		*.1549*	
Prob>chi^2	*.0000*	*.0000*	*.0675*	*.0000*	*.0480*	*.0000*	*.0116*

Table 16. Determinants of Adult Diabetes

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9
	Pooled logit	Pooled logit	Pooled logit	FE logit	Pooled logit	FE logit	FE logit	Pooled logit	FE logit
Age	0.409176***	0.3802748***	0.2527756***	25.10231	0.2587819***	20.53832*	16.83876	0.3071973***	-2.21573
Age^2	-0.0030691***	-0.0028181***	-0.0017596**	-0.07284	-0.0018326**	-0.0190765	-0.0163524	-0.0022413***	0.001358
Household income	0.000000196	0.00000137	0.00000244	3.16E-05	0.00000263	-8.02E-06	0.000018	2.33E-06	7.6E-06
Education	0.0243316	0.0315823	0.0310879		0.0323364	4.516499*		0.019445	0.127828
Married		0.6097977	0.5639137		0.7337991			-0.53337	14.33089
Occupational activity level	-0.8867079***	-0.6083109***	-0.6473759***	-1.61646	-0.64872***	-2.374867*	-1.617772*	-0.3640706***	-0.07578
Housework	-0.230053**	-0.1828483***							
Distance to medical facility	0.0028784		-0.0028407	0.191452					
Distance to park	-0.068749		-0.0542576	-2.20719					
Distance to playground	0.0308934		0.0306638	2.582773					
Owning car	1.232289***							0.7040213**	1.15753
Owning motorcycle	0.1430899							0.001992	-0.45541

Bus in neighbor-hood	-0.3354482							-0.2567376*	0.131188
No. of fast food restaurants	0.0182057				0.0103578	-7.317319	-8.059073		
No. of supermarkets in 5km	-0.0256666				0.0059452	0.3012063*	0.2326809*		
No. of free markets in 5km	0.0274151				0.0114035	-0.6247085	-0.0996575		
Sample size	*2795*	*4568*	*3901*	*58*	*4955*	*72*	*72*	*8817*	*267*
Pseudo R^2	*.1353*	*.1223*	*.1044*		*.1012*			*.0954*	
Prob>chi^2	*.0000*	*.0000*	*.0000*	*.0003*	*.0000*	*.0006*	*.0030*	*.0000*	*.0009*

6. Conclusions

This paper studies the effects of community environment on travel and health in Chinese cities using CHNS, a longitudinal dataset that has been seldom analyzed by researchers outside of the area of public health. Major results are summarized below.

- Household income, size, and accessibility to transit and schools affect motor vehicle ownership, though differently depending on motor vehicle type and city size. Overall, it confirms the important role of income in vehicle ownership, as found by Zegres' (2010) study in Santiago de Chile;

- Increase in household income and ownership of motor vehicle reduce the likelihood of cycling or walking by adult commuters;

- Availability of fast food restaurants in neighborhood and ownership of car increase children's consumption of fast food;

- The numbers of accessible supermarkets and free markets have opposite effects on urban residents' food consumption, measured by intakes of energy, protein, carbohydrate and fat. Income level positively affects intake of protein. Ownership of motorcycle positively affects intake of protein and adult intake of carbohydrate. Neighborhood accessibility to fast food positively affects carbohydrate intake. Older people tend to have less carbohydrate and fat. Occupational activity level positively affects intake of protein, carbohydrate, while negatively affects intake of fat;

- Adult body mass index is affected positively by income and negatively by education level and participation in housework.

Overall, neighborhood food environment, such as access to markets and fast food restaurants, shows significant effects on urban residents' food and nutrition intake, but not significantly on their health outcomes. While some features of the built environment, such as accessibility to transit and schools, show little direct effect on travel behavior, nutrition intake, or health of Chinese urban residents. Nevertheless, evidence suggests that their effects may be indirect, through household vehicle ownership.

Unlike most of the earlier studies, this research avoids the endogenous bias resulting from residential sorting, and provides one of the first sets of empirical evidence on the relationship between land use, travel, and health in the developing world. The precision of measures of income, nutrition intake, and health outcomes are much better than most previous studies in both the developed and developing countries. Results of this study address the literature gap by providing reliable evidence on neighborhood built environment's impacts on passenger travel and public health. Results of this study can inform urban policy decisions regarding land use and siting of public service to facilitate low-impact transportation and healthier lifestyles in China's cities. This is especially valuable given China's rapid income growth and urban restructuring in the recent past and the near future.

Of course, there are limitations of this study, as mentioned previously. For example, the data only allow us to measure the built environment by function (community resource—accessibility to various important destinations), but not by form (e.g., density, design, etc.). In addition, although perhaps less of a concern, self-selected moving out of the sample neighborhoods may bias the results.

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