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Shengyuan ZHANG, Jimin ZHAO, Albert PARK

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HKUST Institute for Emering Market Studies
The Hong Kong University of Science and Technology
Clear Water Bay, Kowloon, Hong Kong
T: +852 3469 2215 E: iems@ust.hk W: iems.ust.hk

Assessing Urban Transport Systems through the Lens of Individual Behavior: Shenzhen and Hong Kong

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Authors' contact information

Shengyuan Zhang
Division of Social Science
Hong Kong University of Science and Technology
E: szhangah@ust.hk
Click here to enter text.

Jimin Zhao
Division of Social Science
Hong Kong University of Science and Technology
E: jiminzhao@ust.hk

Albert Park
Division of Social Science, Department of Economics
Hong Kong University of Science and Technology
E: albertpark@ust.hk

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Jimin Zhao, Shengyuan Zhang, and Albert Park*

Abstract

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*Jimin Zhao (jiminzhao@ust.hk) is Associate Professor of Social Science, HKUST. Shengyuan Zhang (szhangah@ust.hk) is Ph.D. candidate in Social Science, HKUST. Albert Park (albertpark@ust.hk) is Chair Professor of Social Science and Professor of Economics, HKUST. The authors acknowledge support from the Public Policy Research Funding Scheme of the Hong Kong Research Grants Council (HKUST6006-PPR-12).

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1. Introduction

Global energy use and carbon emissions are increasingly concentrated in cities. Urban areas account for 75 per cent of global energy consumption and nearly 80 percent of greenhouse gas emissions (World Bank 2010). Within cities, transportation accounts for between 15% and 40% of total CO_2 emissions, mainly from road transport. In many developing and middle income countries, the transportation sector accounts for the greatest share of the *increase* in carbon emissions because many individuals aspire to own and drive their own vehicles as incomes rise. This has made transportation the most difficult sector to reduce CO_2 emissions (Hickman and Banister 2007; Hickman, Ashiru and Banister 2009a, 2009b, 2010). Designing effective policies to reduce energy use and CO_2 thus depends critically on improved understanding of the transportation decisions of individual citizens.

Because in many countries demands related to income growth create the greatest challenge to limiting transportation energy use, in this study we focus particular attention on examining how income levels influence individual decisions related to transportation. Many emerging markets also are witnessing rapid demographic changes with respect to educational attainment and age structure, which also are key determinants of transport behavior. In many countries, the younger generation are more likely to pursue modern lifestyles that are high in energy consumption and CO_2 emissions (Dimitriou 2006). Quantifying how incomes and demographic factors influence energy use are critical inputs into forecasting and planning models.

A number of studies have examined the determinants of different aspects of travel behavior by analyzing micro-datasets.[1] However, this study is the first to provide a comprehensive empirical framework for analyzing how key individual factors influence energy use and carbon emissions through multiple dimensions of travel behavior. We first show mathematically the influence on total energy use and CO_2 emissions of specific travel-related decisions, including the number of trips, the distance traveled per trip, the mode of transportation, ownership of cars and electric 2-wheel vehicles, and the fuel economy of cars. We then empirically estimate how key individual factors such as income, age, and education influence each of these decisions. This enables us to conduct a decomposition exercise which quantifies the relative importance of different channels through which income, age, and education may influence energy use and carbon emissions. To our knowledge, this study provides the first full accounting of these different channels. As such, it develops a methodology that may be usefully employed in other settings to help experts and policy-makers "unpack" the travel behavior of citizens to enable them to more deeply understand how

[1] Household travel surveys provide essential information about individual travel behaviour (e.g., travel modes, distance, time, and cost) for traffic planners, public transport providers, infrastructure authorities and transport scientists (Choi, J.M., et al., 2014; An, K., et al., 2013; etc.). They have been conducted in many large cities worldwide (e.g., London, Seattle, Washington D.C., Hong Kong) and even at the national level in the United States, the United Kingdom, and New Zealand. The data have been used for planning purposes and for academic research on transport management, energy consumption and carbon emissions (Lee, Hickman, Washington, 2007; Donegan, Adamson, Donegan, 2007; Stopher and Greaves, 2007; Liu and Shen, 2011; Mohammadian, Javanmardi, and Zhang, 2010).

individual travel decisions shape outcomes that in aggregate greatly influence the economic and environmental sustainability of cities and nations.

Another key contribution of this research is that it analyzes a new survey dataset collected by the authors of travel behavior in one of China's most dynamic cities—Shenzhen in Guangdong Province in the heart of the Pearl River Delta, China's most important manufacturing region. The dataset was collected for the purposes of research and so includes quite comprehensive information on the backgrounds of individuals and their travel behavior. It thus is a valuable addition to the handful of datasets on travel behavior that have been collected in mainland China, often for special purposes.[2]

Examining travel behavior in China is of particular interest and importance. Over the past couple of decades, the country has witnessed rapid economic growth and urbanization, the latter fueled by massive internal migration. For some years now, China has been the second largest oil importer in the world after the United States and the largest aggregate CO_2 emitter in the world (IEA, 2014). More new vehicles are sold in China than anywhere else in the world, which is a primary driving force behind China's increasing demand for oil. Many of the world's most polluted cities are in China. The Chinese government wants to tackle these challenges aggressively. The country has set a national target to reduce carbon intensity by 40-45% by

[2] A travel survey was conducted in Beijing for the Olympic Games and in Shanghai for the World Expo (Beijing Transport Commission, 2009). The Beijing Institute of City Planning conducts a relatively large-scale household travel survey once every five years but does not release the data publicly. We are unaware of any large-scale travel surveys conducted in cities in southern China.

2020 compared to 2005. The 12th Five-Year Plan announced targets to reduce energy intensity by 16% and carbon intensity by 17% from 2010 to 2015.

The rest of the paper is organized as follows. In Section 2, we present our analytical framework and empirical analysis strategy. The study site, survey data, and descriptive statistics are introduced in Section 3. Sections 4 and 5 present the main results. Section 4 analyzes the determinants of different aspects of travel behavior. Section 5 quantifies the extent to which income, age, and education influences energy use through different travel-related decisions. A final section concludes.

2. Methodology

We model the transportation energy use by individual i to be a function of a set of transportation-related decisions, each of which may be influenced by individual characteristics X_i. Specifically, we posit the following equation for transportation energy use:

$$E_i = T(X_i) \times D(X_i) \times \sum_{m=1}^{4} [p_m(X_i, V(X_i), D(X_i)) \times e_m(X_i)] \quad (1)$$

Here, E_i is transportation energy use per day by individual i, which is determined by T, the number of trips taken; D, the average distance traveled per trip; p_m, the propensity to use four different transportation modes indexed by m for each trip; V, indicator variables for whether an individual owns a car (or van)[3] or an electric 2-wheel vehicle; and e_m, the energy used per person per unit distance using transportation mode m. Each of the transportation-related decisions affecting total energy use may be influenced by individual characteristics X_i, which includes income, age, education, gender, marital status, and urban location (district). Equation (1) implicitly assumes that individuals first make decisions about the number and distance of trips based on their work and life circumstances, and then select which transportation mode to use for each trip, considering its purpose, distance, and the availability of owned vehicles. Research using Chinese data supports this assumption (Xianyu, 2013). Individuals also make decisions about vehicle ownership (cars and electric 2-wheel vehicles) as well as the fuel economy of the cars that they own. Vehicle ownership influences transportation mode choice and fuel economy affects the energy use per distance traveled by car.

An analogous equation can be written for the determinants of transport-related carbon emissions of individual i (C_i):

$$C_i = T(X_i) \times D(X_i) \times \sum_{m=1}^{4}[p_m(X_i\,, V(X_i), D(X_i)) \times c_m(X_i)] \tag{2}$$

The only difference is that carbon output per unit distance traveled using different transportation modes (m) requires different coefficients than for energy use (c_m instead of e_m).

[3] Hereafter, "cars" also includes passenger vans.

The four transportation modes to be considered include public transportation (subway and buses), non-motorized transport (walking and cycling), electric 2-wheel vehicles (bicycles and motorcycles), and cars. We are particularly interested in the choice between public transportation and cars, which are the most common options and carry the most relevance for meeting policy goals. We assume that e_m is influenced by individual characteristics X_i only for one of the transportation modes--cars, via the gas mileage of cars owned (measured in liters required per kilometer).

Our approach is to estimate regression specifications in which the five transportation decisions affecting energy use, namely D, T, p_m, CAR, and e_m (for passenger cars) are modeled as functions of a common set of covariates, X_i. Examining the determinants of each of these transportation-related decisions is of independent interest for understanding individual transportation behavior and has been the subject of study by others, including in China (for example, Manoja and Vermab, 2013; Xianyu, 2013; Choi et al, 2014; Long and Thill, 2015).

A unique aspect of our study is that we draw direct implications of each of these different decisions for overall energy use and carbon emissions using equations (1) and (2). This enables us to decompose how individual characteristics X_i influence energy use through each of the five transportation decisions, providing a much more complete and richer characterization of how income, education, and age influence these key sustainability outcomes. Using the survey data, we can also calculate the actual energy use of each respondent, and estimate directly the unconditional (reduced-form) relationship between energy use and the individual characteristics of interest.

3. Survey Site and Data

The data used in this study are from a survey conducted by the authors in Shenzhen, China, conducted in the fall of 2014. Shenzhen is located in the Pearl River Delta in southern Guangdong Province. The city is one of China's most successful Special Economic Zones (SEZs) and one of the country's most important manufacturing centers. Since it was established in the early 1980s, it has been one of the fastest-growing cities in the world. The city had a population of 10.78 million residents in 2014, who live in 10 urban districts.

Given its rapid socioeconomic development and high material living standards, Shenzhen serves as an excellent site to study the challenges posed by rapid urbanization in Cjhina, in particular the increase in demand for energy-intensive transportation. The challenges facing Shenzhen are similar to those facing leading cities in China today and likely by many of China's cities in the future. In response, Shenzhen already has made concerted efforts to promote a low-carbon transport system. It is the seventh city in mainland China to build a subway system and is one of six pilot cities for promoting hybrid and battery vehicles through government subsidies.[4]

[4] The central government launched the program in 2010 in six cities including Shenzhen. By 2016, the number had grown to 25 pilot cities.

The survey conducted in Shenzhen was administered through face-to-face interviews of Shenzhen residents aged 15 years or older conducted in all ten of Shenzhen's urban districts, with the assistance of enumerators from a local survey research company. The authors directed the training of enumerators and supervised and monitored the field research. Surveys were conducted of 1015 individuals, with great care taken to ensure that the sample accurately reflected the population distribution (as measured by the 2010 census) with respect to age, education, gender, and district location.[5] Respondents were recruited through two methods: snowball sampling using contact lists of residents kept by the local survey company, and random interviews of individuals approached in key neighborhood locations, such as markets, entrances to apartment complexes, etc.

The survey questionnaire consists of two parts: 1) a general survey, including questions on basic socio-economic characteristics, vehicle ownership, normal usage of different travel modes, and environmental awareness; and 2) a 24-hour trip-diary, which records chronologically the travel information of all the trips made by the respondents during the previous day.[6] The travel information includes the purpose of each trip, the transport modes and time spent on each leg[7] of each trip, the starting and stopping address for each leg of each

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[5] The match between the sample distribution and population distribution (as reflected in the 2010 census) is very close for age, gender, and district location. Respondents were somewhat more educated (just 32% with middle school education or less) than in the 2010 population census (55% with middle school education or less), which could reflect rapid increases in educational attainment or greater difficulty in finding less educated individuals, perhaps because they are more likely to live and work in factories and make fewer trips outside their factory.

[6] Literally, it is from 03:00 am of the day before the interview day (or the trip day) to 03:00 am of the interview day.

[7] The definition of trip and leg is as shown in the following example. Assume a person travel from home to office by bus. The whole process is defined as a trip, which includes three legs. The first leg should be the walk from

trip, and other information such as fares and fees, the number of passengers, parking location, etc.

The departure and arrival addresses are used to calculate the distance from the departure to arrival addresses using the program Baidu map (http://map.baidu.com). For legs using public transportation (bus or subway), the names of routes/lines are recorded and the distance is obtained accordingly. For private transport, such as private cars, motorcycles, or biking and walking, the shortest route is selected among the alternative routes suggested by Baidu map.

Summary statistics for the sample data are provided in Table 1. Of the 1015 respondents interviewed, 19 (less than 2%) did not report taking any trips during the previous day; these observations are dropped when analyzing travel behavior since distance and transportation mode cannot be analyzed. The average number of trips per day is 2.97, including 0.95 work-related trips, 0.84 trips for errands or leisure activities, and 1.18 trips home. The average distance of trips is 6.86 km. The mean distance for work-related trips is 7.50 km, compared to 4.27 km for errands or leisure and 7.14 for trips home.

Respondents were asked to report all trips in which they left their building compound. As seen in Figure 1, most trips (50%) use modes of transportation that are non-motorized (walking, manpowered bicycles). Public transportation accounts for 28% of trips, private cars

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the entrance of the building where his/her home is to the nearby departure bus stop, the second leg be the travelled distance on the bus, and the third leg be the walk from the destination/arrival bus stop to the entrance of the building where his/her office is. In this study, all the successive travels and activities within a single building are not accounted for separately, and regarded as one activity instead.

and taxis account for 16%, and electric 2-wheel vehicles account for 6%. None of the survey respondents reported using gas-fueled motorcycles, reflecting the city's policy to ban such vehicles and only permit electric bicycles and motorcycles (Zhen, 2013). The survey revealed that 37% of respondents or members of their household owned cars, while 16% owned electric 2-wheel vehicles. The average fuel economy of owned cars was 8.0 L/100 km.

The analysis in this paper focuses on the impacts of income, age, and education on travel behavior. As reported in Table 1, the average monthly income of respondents was 5282 RMB (or US$852 based on official exchange rates at the time of the survey). 9% of respondents reported earning zero income, including those who were retired, in school, unemployed, or homemakers. Shenzhen is a city of migrants from all over China, so has a relatively young population. The mean age of respondents was 32.2, with 34% of the sample aged 15 to 25, 33% aged 16 to 35, 21% aged 36 to 45, 7% aged 46 to 54, and 5% above age 55. These population shares are nearly identical to those found in the 2010 population census (reference). With regards to educational attainment, 32% of the sample have a middle school education or below, 38% have completed high school, 18% have completed vocational college, and 11% are regular college graduates. Table 1 also reports the distribution of the sample across Shenzhen's 10 urban districts; these shares also are very close to the population shares reported in the 2010 census.

4. Determinants of Travel Behavior

In this section, we present the results of regression analysis that assesses how the key individual characteristics of interest impact 6 travel-related decisions: frequency of trips, distance of trips, transportation mode, car ownership, electric 2-wheel vehicle ownership, and fuel economy of cars. Each of these behaviors influences energy use and carbon emissions as described in Equations (1) and (2). The regressions use different model specifications depending on the nature of the dependent variables (i.e., Ordinary Least Squares (OLS), Probit, Multinomial Logit).

All of the regressions control for gender (dummy for male) and marital status (dummy for being married), as well as location (dummy variables for each urban district). To measure income, the controls include a dummy variable for whether the respondent has positive income and we capture the income effect by including the interaction of that dummy and ln(monthly income).[8] Respondents who report no income are not necessarily deprived relative to those with positive income, for example they are more likely to report owning cars (mainly retired persons). Age and education are captured by sets of dummy variables. The omitted (reference) categories are the youngest age group (age 15 to 25) and the lowest educational attainment group (middle school and below).

[8] The survey also collected categorical data on household incomes, but these were consistently found to lack statistical significance when included in the regressions, suggesting that such incomes are poorly measured or lack explanatory power.

Trip frequency. Results for the determinants of the number of trips taken are presented in Table 2. For all trips (regardless of purpose), income and all of the education variables are significant at the 95% confidence level (column 1). It is unclear what should be the predicted impact of income on trip number, as higher incomes may be associated with jobs that require more or less travel. Higher income also increases spending power but at the same time increases the opportunity cost of time spent on leisure or errands. The point estimate suggests that a 10% increase in income increases the total number of trips by 0.0169 (or 0.5% of the mean number of trips), a modest effect. Analysis of activity-specific trips (columns 2-4) show that the positive income effect is driven by work-related trips, suggesting that those with higher paying jobs (controlling for education) are required to travel more frequently for work.

The number of trips appears to have a U-shaped relationship with age, being the least for those aged 36 to 45, although only the dummy for this age group has a statistically significant coefficient. As seen in the results for specific types of activities, the U-shaped age pattern is driven by differences in leisure and errand trips (column 3). Young adults may have a greater taste for social activity and may have a lower opportunity cost of time, both with respect to wages and family demands on their time. Older persons are more likely to be retired and thus have more time for leisure and errand activities, although their work trips decline (column 2).

Education has a strong negative relationship with the number of trips. Compared with those with middle school education or less, college graduates have 0.363 fewer visits (22% of the mean number of trips). The activity-specific results show that this pattern is mostly driven by differences in work trips. More educated workers thus have jobs that require fewer trips, perhaps due to fewer working days per week or more stable working hours.

Trip distance. Next, we regress the log of distance per trip on the same standard set of covariates. Results are reported in Table 3. Nearly all of the coefficients are highly statistically significant, and the main patterns for all trips (column 1) are driven primarily by impacts on the distance of work-related trips (reported in column 2). The elasticity of distance with respect to income is 0.253 for all trips and 0.251 for work-related trips. This means that a 10% increase in income increases distance per trip by 2.53%. One possible explanation is that individuals with higher incomes may be able to afford and have a greater taste for higher quality housing which requires them to commute farther for work. For instance, frontline production workers in factories may prefer housing that is low-price, low-quality and located near to their workplace.

Trip distance increases significantly with age, with the exception of the oldest group (column 1). Again, the results are driven by impacts on the distance of work-related trips, consistent with the idea that older workers are more willing to travel farther to work in order to find more desirable living environments. Those aged 46 to 55 travel 39.5% further per trip than the youngest workers (age 15 to 25).

The magnitudes of the effects of education on trip distance are very large, positive, and highly statistically significant. Education is a more important determinant of travel distance than income or age. Vocational and regular college graduates travel 65.6% and 63.8% farther per trip than those with middle school education or below (column 1 of Table 3). These magnitudes are driven nearly entirely by longer work-related trips (column 2) but also are consistent with the pattern of trips for leisure or errands (column 3). This is consistent with distinct lifestyle preferences of more educated individuals to put up with longer work commuting costs to find better living environments. In China, many workers with lower levels of education are migrant workers whose top priority is to make money rather than seek out better and more expensive living environments.

Transportation mode. Perhaps the most important decision affecting energy use and carbon emissions is whether to use public transportation or drive one's own car. Non-motorized transport (walking and manual bicycles) generally is used only for short-distance trips, and driving electric 2-wheel vehicles is not a very common travel method. In order to study the choice of transportation mode, we estimate a multinomial logit model that allows for four choices: public transport (the reference category), non-motorized transport, electric 2-wheel vehicles, and cars.[9] The full set of coefficients (other than for district dummies) from this estimation are reported in Appendix Table 1. In addition to the standard set of covariates, we also include ln(distance per trip), dummies for car ownership and electric 2-wheel vehicle ownership, and controls for travel during rush hour, travel on the weekend, and various trip purposes. Using the estimated coefficients for the multinomial logit model, it is possible to calculate marginal probabilities for the estimation sample, by averaging the change in probabilities of each possible outcome across observations given a change in the value of the covariate. Results are reported in Table 4.

We focus on the impacts of income, age, and education on the likelihood of taking public transportation and driving passenger cars (columns 3 and 4). Income has a positive and significant, but relatively small direct impact on the probability of driving a car, and a negative but small and statistically insignificant impact on the probability of taking public transportation. A 10% increase income increases the likelihood of driving a car by only 0.34%.

The older the individual, the more likely he or she will drive a car and the less likely he or she will take public transportation, except for the oldest group. Compared to those aged 15 to 25, the probability of driving a car is 3.9%, 5.0%, and 5.4% greater for those aged 26 to 35,

[9] The multinomial logit model makes the strong assumption of independence of irrelevant alternatives (IIA), that the choice between two options is not affected by the availability of other options. Since the most important choice affecting energy use and carbon emissions is between public transportation and driving cars, and this choice is unlikely to be strongly influenced by being able to walk or bicycle manually (only realistic for short distances) or driving electric 2-wheel vehicles (uncommon), relaxing the IIA assumption is unlikely to significantly alter our main findings.

36 to 45, and 46 to 55 while the probability of taking public transportation is 5.4%, 5.6%, and 7.4% lower for the same age groups.

When it comes to education, the only group that behaves significantly different than other groups is college graduates, who are 11.4% more likely to drive passenger cars, 6.9% more likely to take public transportation, 27.9% more likely to take non-motorized transport, and 46.2% *less* likely to drive an electric 2-wheel vehicle. These results suggest that the preferences of college graduates regarding transportation modes is quite different from those of non-college graduates.

The results presented in Table 4 show that vehicle ownership plays a major role in transportation mode choice. Owning a car increases the probability of driving a car by 19.9% and reduces the probability of taking public transport or non-motorized transportation by 14.1% and 4.8%, respectively. Owning an electric 2-wheel vehicle increases the probability of traveling using an electric 2-wheel vehicle by 11% and reduces the probability of non-motorized transport by 9.9%, with little impact on driving a car or taking public transportation.

When the trip distance increases by 10%, the probability of taking non-motorized transport falls by 1.67% and the probabilities of taking public transportation or driving cars increases by 1.18% and 0.43%. As described above, trip distance is significantly affected by income, age, and education, as is vehicle ownership. Therefore, these factors affect transportation mode use both directly and indirectly through their impact on vehicle ownership (cars and electric 2-wheel vehicles) and trip distance, which also affect transportation mode choice. As a result, there are four separate channels through which income, age, and education may influence transportation mode choice.

Vehicle ownership. In the first two columns of Table 5, we report the estimation results for probit models of the determinants of ownership of electric 2-wheel vehicles and cars. For the former, we find no evidence of income effects and suggestive evidence that younger groups (below age 35) are much more likely to own electric 2-wheel vehicles (column 1). College graduates are 8.7% less likely to own such vehicles than those with middle school education or less, a relationship that is highly statistically significant.

For car ownership, we find a large and significant impact of both income and education on the latter (column 2 of Table 5). An increase in income by 10% increases the probability of car ownership by 2.9 percent (compared to an overall ownership rate of 37%). We also find that those above age 55 are 32.2% more likely to own a car than the youngest age group (age 15 to 25). None of the other age categories show statistically significant differences.

The education impacts are more pronounced than for income or age. College graduates are 28.1% more likely to own a car than those with middle school education or less, even after controlling for income differences. Clearly, more educated persons have a motivation to purchase cars that goes beyond the effect of having higher incomes, perhaps stemming from lifestyle considerations.

Fuel economy. Finally, we examine the determinants of the fuel economy of private cars, measured in liters per km. Thus, a higher value reflects poorer fuel economy. The survey asked respondents to report the fuel economy of all owned vehicles, so this regression is run using the subsample of 378 respondents who reported owning a vehicle. We find that higher income substantially increases fuel use per distance traveled. The elasticity of fuel economy with respect to income is 1.25, which means that for every 1% increase in income, fuel required per km increases by 1.25% (column 3 of Table 5). None of the age or education dummy variables have coefficients that are statistically significant.

5. Decomposition Analysis for Impacts on Energy Use and Carbon Emissions

Having gained some insight into how key characteristics affect multiple dimensions of travel behavior, in this section we return to equations (1) and (2) and bring the results together to quantify and decompose the different channels through which income, age, and education may influence energy use and carbon emissions.

To motivate our approach to the decomposition exercise, we take logs of both sides of equation (1) and differentiate with respect to the variable X_i. This yields the following:

$$\frac{dlnE_i}{dX_i} = \frac{\partial lnT_i}{\partial X_i} + \frac{\partial lnD}{\partial X_i} + \frac{\partial lnP}{\partial X_i}, \tag{3}$$

where

$$P_i = \sum_{m=1}^{4}[p_m(X_i\,, CAR(X_i)\,, D(X_i)) \times e_m(X_i)]. \tag{4}$$

The left hand side of (3) is approximately the percentage change in energy use caused by a one unit change in X_i. It is the sum of the impacts of X_i on number of trips, distance per trip, and the energy intensity of different transport modes weighted by the propensity to use different modes. Further, as seen in equation (4) the impact of X_i on the probability of using a specific transportation mode has four components: a direct effect and three indirect effects that depend upon how X_i affects car ownership, ownership of electric 2-wheel vehicles, and distance per trip, multiplied by the impact of these factors on transportation mode choice. For passenger vehicles, a fourth indirect effect of X_i is through the effect on the energy intensity of distance traveled via changes in fuel economy. The decomposition of impacts on carbon emissions follows analogously. See the Appendix for more details on the decomposition formulas.

Estimating the impact of travel behavior on energy use and carbon emissions depends critically on the coefficients used to estimate energy use and carbon emissions per distance traveled using different transportation modes. Our estimates of these coefficients are based on various calculations using the survey data as well as secondary information about bus energy use in Shenzhen and energy used for electricity production in Guangdong. The coefficients are reported in Table 6. They make obvious the fact that much more energy is used and carbon emitted when using passenger cars than any other transportation mode. Nearly 10 times more energy is used driving private cars compared to public transportation, and over 5 times as much

CO_2 is emitted. Travel using electric 2-wheel vehicles is extremely energy efficient and clean, using more than 70% less energy and emitting more than 50% less CO_2 in comparison to public transportation. Thus, the key to influencing transportation energy use and carbon emissions is to affect the use of passenger cars.

The results of decomposition analysis for impacts on energy use and carbon emissions are presented in Tables 7A and 7B. Turning first to the results for energy use, we find that by far the most important channels through which income, age, and education influence energy use are distance per trip and the use of cars. For cars, we decompose the impacts of the X's into the direct effect and four indirect effects (via distance, ownership of cars, ownership of electric 2-wheel vehicles, and fuel economy). Because of their relatively minor importance, we do not separately report the direct and indirect effects for other transportation mode choices.[10]

When we add up all of the effects of income on energy use through its various channels, we estimate an elasticity of energy use with respect to income of 0.916 (last column of Table 7A), which means that a 10% increase in income increases energy use by about 9.16%. Thus, energy use increases roughly in proportion to income. Examining which channels are most important in explaining this effect, we find that the largest impact is from increased driving of cars (elasticity of 0.623), followed by distance per trip (0.253), then number of trips (0.057). Much of the income elasticity accounted for by increased driving of cars comes from greater

[10] These results are available from the authors upon request.

car ownership (0.303), followed by direct effects (0.177), worse fuel economy (0.084), and distance traveled (0.057).

The estimated total effects of age on energy use reported in the last column of Table 7A shows that energy use increases with age, except for the oldest group (above 55) for whom we see a drop. Compared to the youngest group, those aged 46 to 55 consume 62.4% more energy for transportation. The decomposition results show that this difference is driven primarily by longer trip distance (39.5%) and direct effects on greater use of passenger vehicles (28.1%).

One of the most interesting and important findings of this study is the very large positive impacts of educational attainment on energy use, even after controlling for income. The estimated total effects (last column of Table 7A) show that college graduates consume 157% more energy than those with middle school education and below. Thus, education may be an even more important factor than income in explaining differences in transportation energy consumption. Since these differences cannot be explained by income differences, they must be associated with lifestyle preferences. By far the largest channel for this effect is the greater propensity of college graduates to drive cars (accounting for 106.8% of the 157% gap). The car effect is mainly due to the direct effect of education on driving passenger vehicles (59.3%), followed by car ownership (29.1%), distance traveled (14.3%), and worse fuel economy (4.7%). In addition, there is a large impact of graduating from college on energy through greater distance traveled per trip (accounting for 63.8% higher energy use), which likely reflects the willingness of college graduates to commute farther to enjoy better living environments.

The decomposition results for carbon emissions are qualitatively similar to those for energy use, since generally speaking behaviors that increase energy use also increase carbon emissions. In fact, the impacts of the trips and distance on carbon emissions is exactly the same as for energy use, which is apparent from inspecting equations (1), (2), and (3). Overall the impacts of changes in income, age, and education on carbon emissions are a bit muted compared to energy use, because the carbon emission differences among transportation modes are not as great as the energy use differences (Table 6). For example, the elasticity of carbon emissions with respect to income is 0.823 compared to 0.916 for energy use, those aged 46 to 55 produce 57.6% more carbon emissions than those aged 15 to 25, compared to 62.4% energy use, and college graduates produce 136.3% more CO2 than those with middle school education and below compared to 156.7% more energy use. The fact that the impact of distance per trip on carbon emissions is the same as for energy use implies that it accounts for a greater share of impacts on carbon emissions than of impacts on energy use.

A simpler way to estimate the total impacts of income, age, and education on energy use or carbon emissions is to first calculate the energy used or carbon emitted by each individual based on his reported trip number, distance traveled, transportation mode choices, and energy intensity (based on reported gas mileage, number of passengers in cars, buses, and subway cars) and then regress individual ln(energy use) or ln(carbon) directly on the standard set of covariates (X_i). We report the results of such regressions in Table 8. Given the many approximations used in the decomposition exercise, we do not expect the reduced form estimates of total impacts of changes in X_i to be identical to the aggregated impacts on different travel behaviors that influence energy use. Nonetheless, it is reassuring that the reduced form results reported in Table 8 do not depart dramatically from the estimated impacts reported in the last column of Table 7A. The estimated elasticity of energy use (carbon emissions) with respect to income is 1.139 (1.131) in the reduced form regressions compared to 0.916 (0.823) in the decomposition exercise. The estimated effects of age are of similar magnitude but peak for the 36 to 45 year olds (in the regression) rather than the 46 to 55 year olds (from the decomposition results). The difference in energy consumption (carbon emission) of college graduates compared to those with middle school education and below is very similar in the regressions—155.1% (154.7%)--and in the decomposition exercise--156.7% (136.3%). Although the regressions in principle produce more accurate estimates of the overall impacts of income, age, and education on energy use, for many purposes, especially when assessing policies, understanding the different pathways through which the aggregate impact is produced is of critical importance.

6. Conclusions

Many developing countries and emerging markets are severely challenged by rapid increases in energy consumption for urban transportation fueled by the aspiration of citizens to own and drive cars. Rapid income growth and demographic changes (educational attainment and age structure) strongly influence various individual travel behaviors, but the exact nature of these effects and their relevance for aggregate energy use and carbon emissions has been obscure. In this study, we provide a comprehensive framework for conducting such an analysis, and apply the methodology using survey data collected by the authors in Shenzhen, China, one of China's most dynamic cities.

We find that energy use and carbon emissions increase almost proportionally to income, and that age and especially education also have large impacts on both outcomes. For income, greater car ownership leading to more driving of passenger cars explains about one third of the income effect, followed by longer trip distances with higher incomes, and direct income effects on driving cars. Age effects are driven mostly by longer trip distances, with greater propensity of driving cars also playing an important role.

An important result is the sizable positive impact of education on energy use and carbon emissions. College graduates consume more than 150% more energy than those with middle school education and below, an effect driven by the much greater propensity of college graduates to drive cars, travel farther for work, and own cars. Since these estimates control for income effects, we conclude that highly educated citizens have strong lifestyle preferences to drive cars and commute farther to work, perhaps in order to find better living environments. Thus, it does not appear that more educated citizens have heightened awareness of the need to address environmental problems, at least not in a way that strongly influences their actions. In fact, they are more likely to own cars with worse fuel economy. Absent the imposition of stringent measures to control behavior, this could pose substantial challenges for limiting future increases in energy consumption and carbon emissions, since Shenzhen is aggressively seeking to attract more educated workers to develop high-tech industries and services and to maintain rapid GDP (and income) growth.

These insights into individual travel behavior in Shenzhen should help policy makers in Shenzhen and elsewhere focus attention on policies that can target behaviors that have the largest impact on energy use and carbon emissions. The methodology we have developed can be applied to a wide variety of settings to illuminate how individual travel behavior impacts the sustainability of different urbanization paths.

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Appendix. Decomposition formulas.

Starting with equation (3), we note that $\frac{\mathrm{dlnY_i}}{\mathrm{dX_i}} = \frac{\frac{\partial \mathrm{Y}}{\partial \mathrm{X_i}}}{\mathrm{Y}}$. This means that we can rewrite equation (3) as follows:

$$\frac{\mathrm{dlnE_i}}{\mathrm{dX_i}} = \frac{\frac{\partial \mathrm{T}}{\partial \mathrm{X_i}}}{\mathrm{T}} + \frac{\partial \mathrm{lnD}}{\partial \mathrm{X_i}} + \frac{\frac{\partial \mathrm{P}}{\partial \mathrm{X_i}}}{\mathrm{P}}, \tag{A1}$$

to make the formulation of each element accord with how the dependent variables are defined in the different regressions. For example, $\frac{\partial \mathrm{T}}{\partial \mathrm{X_i}}$ is the coefficient of the linear regression of trip number (T) on X_i, while $\frac{\partial \mathrm{lnD}}{\partial \mathrm{X_i}}$ is the coefficient of the linear regression of the log of trip distance on X_i. To evaluate equation (A1), we take the sample means for T (2.97) and P (0.0075), where P is the weighted average of the energy use coefficients e_m, with weights equal to the shares of sample trips using each mode. The numerator of the last term of equation (A1) is derived from equation (4): $P_i = \sum_{m=1}^{4}[p_m(X_i\,, CAR(X_i)\,, D(X_i)) \times e_m(X_i)]$. To evaluate the direct and indirect effects of X on p_m, we hold e_m constant at the sample mean and take the marginal effects of X_i, ln(distance), car ownership, and electric 2-wheel vehicle ownership on the probability of different mode choices from Table 4, and multiply the marginal effects of ln(distance), car ownership, and electric 2-wheel vehicle ownership with the coefficients on X_i when these three factors are regressed on X_i (first 3 columns of Table 5). To evaluate the impact of X_i on fuel economy of distance traveled by car (e_{car}), we take the coefficient of the regression of e_{car} on X_i (last column of Table 5), divide by the sample mean of e_{car} (=8.0) to calculate the proportional effect on fuel economy, then multiply by the total impact of X_i on p_{car} (summing direct and indirect effects). The formula for decomposing the impacts of X_i on carbon emissions is entirely analogous.

Figure 1. Trip Main Transportation Modes

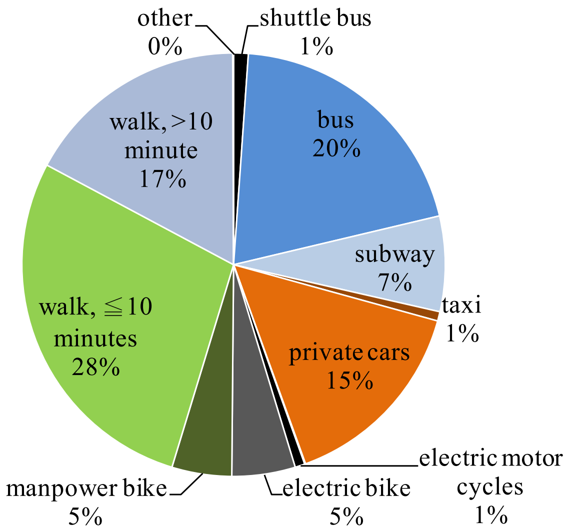

Table 1. Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max
Energy use, MJ/person/day	996	16.1	52.3	0.0	830.1
Ln(1000*energy use)	996	6.2	3.4	2.2	13.1
Emission, kgCO2/person/day	996	993	2742	0.0	32931
Ln(1000*emission)	996	10.5	3.4	6.4	17.3
Number of trips (previous day)	996	2.97	1.24	1	8
Number of trips, work-related	996	0.95	0.79	0	5
Number of trips, leisure and errands	996	0.84	0.90	0	5
Number of trips, to home	996	1.18	0.48	0	4
Ln(1000*tdistance)	996	8.00	1.38	3.91	11.07
Average distance per trip, km	996	6.86	8.99	0.05	64.2
Average distance per trip, work-related, km	707	7.50	9.03	0.1	45.4
Average distance per trip, leisure and errands, km	577	4.27	8.10	0.03	64.2
Average distance per trip, return home, km	975	7.14	9.77	0.03	58.6
Dummy, =1 if own a car	1015	0.37	0.48	0	1
Fuel economy of cars, L/100km	378	8.00	4.21	0	40
Dummy, =1 if owned an electric two-wheel	1015	0.16	0.37	0	1
Monthly income, yuan	1015	5282	8105	0	200000
Dummy, =1 if inc>0	1015	0.91	0.29	0	1
Ln(income)	1015	7.6	2.5	0	12
Dummy, =1 if male	1015	0.54	0.50	0	1
Age of the respondent	1015	32.2	11.2	15	77
Age category	1015	2.16	1.11	1	5
=1, ≦25	345	0.34			
=2, 26-35	332	0.33			
=3, 36-45	218	0.21			
=4, 46-55	74	0.07			
=5, ≧55	46	0.05			
Educational attainment	1015	2.09	0.98	1	4
=1, ≦middle	327	0.32			
=2, high and vocational high	387	0.38			
=3, vocational college	185	0.18			
=4, ≧college	116	0.11			
Dummy, =1 if married	1015	1.6	0.5	1	3
Dummy, =1 in Futian District	1015	0.13	0.34	0	1
Dummy, =1 in Luohu District	1015	0.09	0.28	0	1
Dummy, =1 in Nanshan District	1015	0.10	0.31	0	1
Dummy, =1 in Yantian District	1015	0.02	0.14	0	1
Dummy, =1 in Baoan District	1015	0.25	0.43	0	1
Dummy, =1 in Longgang District	1015	0.18	0.38	0	1
Dummy, =1 in Guangming District	1015	0.05	0.21	0	1
Dummy, =1 in Pinshang District	1015	0.03	0.17	0	1
Dummy, =1 in Longhua District	1015	0.14	0.35	0	1
Dummy, =1 in Dapeng District	1015	0.02	0.12	0	1

Table 2. Determinants of Number of Trips per Day

	(1) All trips	(2) Work related trips	(3) Leisure and errand trips	(4) Trips returning home
Income>0	-0.995	-0.737*	-0.507	0.248
	(0.677)	(0.405)	(0.432)	(0.268)
Ln(income)	0.169**	0.203***	-0.012	-0.022
	(0.081)	(0.049)	(0.051)	(0.031)
Age 26-35	0.005	0.027	-0.052	0.030
	(0.114)	(0.065)	(0.079)	(0.037)
Age 36-45	-0.223*	-0.046	-0.190**	0.013
	(0.133)	(0.077)	(0.090)	(0.045)
Age 46-55	-0.124	-0.053	-0.065	-0.006
	(0.173)	(0.107)	(0.123)	(0.068)
Age >55	0.133	-0.787***	0.673***	0.248**
	(0.224)	(0.094)	(0.147)	(0.109)
High school	-0.217**	-0.058	-0.039	-0.120***
	(0.100)	(0.053)	(0.068)	(0.039)
Vocational college	-0.296**	-0.084	-0.042	-0.170***
	(0.119)	(0.065)	(0.082)	(0.043)
College	-0.363***	-0.167**	-0.100	-0.096*
	(0.137)	(0.080)	(0.095)	(0.056)
Male	0.019	0.137***	-0.098*	-0.020
	(0.081)	(0.046)	(0.058)	(0.030)
Married	0.035	-0.028	-0.005	0.068**
	(0.104)	(0.059)	(0.072)	(0.033)
Observations	996	996	996	996
R-squared	0.051	0.225	0.101	0.075

Notes: Results of Ordinary Least Squares regressions. Robust standard errors in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. All regressions include dummy variables for each urban district. Reference category for age group dummies is "Age 15-25" and for education is "Middle school and below".

Table 3. Determinants of Distance per Trip (logs)

	(1) All trips	(2) Work related	(3) Leisure and errand	(4) Return home
Income>0	-1.896***	-2.970***	0.138	-1.570**
	(0.720)	(0.991)	(0.977)	(0.782)
Ln(income)	0.253***	0.251**	-0.061	0.214**
	(0.086)	(0.110)	(0.117)	(0.094)
Age 26-35	0.211*	0.343**	0.092	0.155
	(0.121)	(0.141)	(0.174)	(0.132)
Age 36-45	0.296**	0.469***	0.282	0.246
	(0.141)	(0.168)	(0.216)	(0.151)
Age 46-55	0.395*	0.593**	0.326	0.564**
	(0.203)	(0.249)	(0.283)	(0.225)
Age >55	-0.040	-0.052	0.370	-0.072
	(0.228)	(0.716)	(0.286)	(0.245)
High school	0.298***	0.342***	0.311**	0.338***
	(0.103)	(0.128)	(0.140)	(0.107)
Vocational	0.656***	0.734***	0.168	0.840***
college	(0.126)	(0.145)	(0.192)	(0.137)
College	0.638***	0.618***	0.560***	0.777***
	(0.149)	(0.200)	(0.206)	(0.158)
Male	0.093	0.006	0.061	-0.017
	(0.089)	(0.106)	(0.128)	(0.095)
Married	-0.111	-0.002	-0.186	-0.163
	(0.111)	(0.126)	(0.170)	(0.120)
Observations	996	704	575	970
R-squared	0.104	0.128	0.074	0.100

Notes: Results of Ordinary Least Squares regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include dummy variables for each urban district. Reference category for age group dummies is "Age 15-25" and for education is "Middle school and below".

Table 4. Marginal Effects on Probability of Using Different Transportation Modes

	Non-motorized	Electric 2-wheel	Public Transport	Cars
Ln(income)	-0.014	-0.001	-0.019	0.034***
	(0.014)	(0.011)	(0.014)	(0.013)
Age 26-35	0.004	0.011	-0.054***	0.039**
	(0.019)	(0.014)	(0.019)	(0.02)
Age 36-45	0.009	-0.003	-0.056***	0.05***
	(0.022)	(0.017)	(0.02)	(0.02)
Age 46-55	0.032	-0.012	-0.074***	0.054*
	(0.036)	(0.026)	(0.026)	(0.032)
Age >55	0.088**	-0.053	-0.062	0.027
	(0.045)	(0.047)	(0.04)	(0.035)
High school	-0.003	0.003	0.021	-0.021
	(0.017)	(0.014)	(0.017)	(0.018)
Vocational	-0.026	-0.01	0.028	0.007
college	(0.021)	(0.016)	(0.02)	(0.019)
College	0.279***	-0.462***	0.069***	0.114***
	(0.039)	(0.046)	(0.025)	(0.026)
Ln(distance)	-0.167***	0.006*	0.118***	0.043***
	(0.004)	(0.003)	(0.005)	(0.004)
Own car	-0.048***	-0.01	-0.141***	0.199***
	(0.017)	(0.012)	(0.012)	(0.013)
Own electric	-0.099***	0.11***	-0.021	0.011
bicycle	(0.017)	(0.012)	(0.018)	(0.017)
Psuedo R2		0.6568		
Observations		2,938		

Notes: Marginal probabilities calculated from the results of estimating a multinomial logit model. Additional regressors not reported in this table include: dummy variable for income>0, male, married, dummy variable for whether the day was on a weekend, dummy variable for whether travel occurred during rush hour, dummy variables for trip purposes, and dummy variables for each urban district. See Appendix Table to see all coefficients. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. eference category for age group dummies is "Age 15-25" and for education is "Middle school and below".

Table 5. Determinants of Electric 2-wheel Vehicle Ownership, Car Ownership, and Fuel Energy Intensity

	(1) Electric 2-wheel Vehicle Ownership	(2) Car Ownership	(3) Fuel Economy L/(100 km)
	Probit	Probit	OLS
Income>0	-0.239	-0.856***	-8.684***
	(0.281)	(0.022)	(2.990)
Ln(income)	0.033	0.293***	1.250***
	(0.021)	(0.039)	(0.339)
Age 26-35	0.011	-0.074	-0.259
	(0.031)	(0.045)	(0.605)
Age 36-45	-0.056*	0.053	-0.205
	(0.031)	(0.054)	(0.602)
Age 46-55	-0.065	-0.045	-0.874
	(0.040)	(0.072)	(1.019)
Age >55	-0.055	0.322***	-0.130
	(0.049)	(0.093)	(0.935)
High school	0.001	0.191***	-0.140
	(0.027)	(0.041)	(0.573)
Vocational	-0.032	0.236***	0.046
college	(0.030)	(0.053)	(0.582)
College	-0.087***	0.281***	0.365
	(0.029)	(0.062)	(0.621)
Male	0.014	0.023	0.793*
	(0.024)	(0.034)	(0.472)
Married	0.034	0.183***	0.343
	(0.028)	(0.040)	(0.533)
Observations	1,015	1,015	378
R-squared	0.0703	0.1829	0.139

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Columns (1) and (2) report marginal probabilities from probit model estimation. Column (3) is from Ordinary Least Squares regression. All regressions include dummy variables for each urban district. Reference category for age group dummies is "Age 15-25" and for education is "Middle school and below".

Table 6. Energy Use and Carbon Emission for Distance Traveled by Main Transportation Model

	Energy Use kg oil equivalent/ km/person	Carbon Emission kgCO2/km/person
Public transport	0.0041	0.0221
Cars	0.0390	0.1128
Electric 2-wheel vehicles	0.0012	0.0092

Notes: We first calculate the coefficients for energy consumption required when traveling using different transportation modes, measured in kgoe/km/person. Estimates are calculated from the survey data, based on fuel consumption per travelled distance per vehicle, in kgoe/(km.vehicle), divided by the average number of passengers per vehicle. Carbon emissions (in kgCO2/km/person) is calculated similarly depending on energy type. To estimate the energy use per km/person for different main transportation modes, we make a slight adjustment to account for the fact that a trip using one main transportation mode may include legs using other transportation modes. This adjustment has almost no impact, because using more than one motorized transport mode is very rare. Among the 870 trips with main mode by public transport (PT in the table), 3 trip included legs using electric bicycles, and among 449 trips by passenger (PC in the table), 2 include legs using public transportation (PT).

Table 7A. Decomposition of Impacts of Income, Age, and Education on Energy Use

	Trips	Distance/trip	2-wheel vehicle	Public transport	Passenger car	Of which: direct	Of which: via distance	Of which: via car ownership	Of which: via 2-wheel ownership	Of which: via fuel economy	Total
Ln(income)	0.057	0.253	0.000	-0.017	0.623	0.177	0.057	0.303	0.002	0.084	0.916
Age 26-35	0.002	0.211	0.002	-0.010	0.168	0.203	0.047	-0.077	0.001	-0.006	0.373
Age 36-45	-0.075	0.296	-0.001	-0.015	0.368	0.260	0.066	0.055	-0.003	-0.010	0.573
Age 46-55	-0.042	0.395	-0.003	-0.011	0.284	0.281	0.088	-0.047	-0.004	-0.035	0.624
Age >55	0.045	-0.040	-0.010	-0.061	0.454	0.140	-0.009	0.333	-0.003	-0.007	0.388
High school	-0.073	0.298	0.000	0.016	0.152	-0.109	0.067	0.198	0.000	-0.003	0.394
Vocational college	-0.100	0.656	-0.002	0.040	0.428	0.036	0.147	0.244	-0.002	0.002	1.022
College	-0.122	0.638	-0.075	0.058	1.068	0.593	0.143	0.291	-0.005	0.047	1.567

Note: See text and Appendix for explanation of calculation method.

Table 7B. Decomposition of Impacts of Income, Age, and Education on Carbon Emission

	Trips	Distance/trip	2-wheel vehicle	Public transport	Passenger car	Of which: direct	Of which: via distance	Of which: via car ownership	Of which: via 2-wheel ownership	Of which: via fuel economy	Total
Ln(income)	0.057	0.253	0.000	-0.028	0.540	0.153	0.049	0.263	0.002	0.073	0.823
Age 26-35	0.002	0.211	0.005	-0.017	0.146	0.176	0.041	-0.066	0.001	-0.005	0.347
Age 36-45	-0.075	0.296	-0.003	-0.024	0.319	0.226	0.057	0.048	-0.003	-0.008	0.513
Age 46-55	-0.042	0.395	-0.006	-0.017	0.246	0.244	0.077	-0.040	-0.003	-0.030	0.576
Age >55	0.045	-0.040	-0.023	-0.098	0.394	0.122	-0.008	0.289	-0.003	-0.007	0.277
High school	-0.073	0.298	0.001	0.026	0.132	-0.095	0.058	0.171	0.000	-0.002	0.384
Vocational college	-0.100	0.656	-0.004	0.064	0.371	0.032	0.127	0.212	-0.002	0.002	0.987
College	-0.122	0.638	-0.173	0.094	0.926	0.514	0.124	0.252	-0.004	0.040	1.363

Note: See text and Appendix for explanation of calculation method.

Table 8. Reduced Form Estimates of Impact of Income, Age, and Education on Energy Use

	(1)	(2)
	Ln(energy use)	Ln(emission)
Income>0	-8.529***	-8.460***
	(1.862)	(1.861)
Ln(income)	1.139***	1.131***
	(0.223)	(0.223)
Age 26-35	0.285	0.285
	(0.290)	(0.291)
Age 36-45	0.729**	0.727**
	(0.351)	(0.351)
Age 46-55	0.485	0.483
	(0.486)	(0.486)
Age >55	-0.336	-0.343
	(0.606)	(0.605)
High school	0.662***	0.663***
	(0.255)	(0.255)
Vocational college	1.396***	1.397***
	(0.308)	(0.308)
College	1.551***	1.547***
	(0.398)	(0.398)
Male	0.465**	0.458**
	(0.214)	(0.214)
Married	-0.048	-0.056
	(0.274)	(0.274)
Observations	996	996
R-squared	0.140	0.139

Notes: Results of Ordinary Least Squares regressions. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include dummy variables for each urban district. Reference category for age group dummies is "Age 15-25" and for education is "Middle school and below".

Appendix Table 1. Determinants of Transportation Mode, Coefficients of Multinomial Logit Model

	Coefficients (Base: Public Transport)		
	Non-motorized	Electric 2-wheel Vehicle	Car
Income>0	-0.8	14.925***	-4.347*
	(2.033)	(3.393)	(2.279)
Ln(income)	-0.033	0.072	0.621**
	(0.244)	(0.409)	(0.258)
Age 26-35	0.537*	0.889*	0.981***
	(0.308)	(0.517)	(0.379)
Age 36-45	0.539	0.453	1.134***
	(0.348)	(0.643)	(0.381)
Age 46-55	0.915*	0.38	1.320**
	(0.521)	(0.956)	(0.539)
Age >55	1.281**	-0.921	0.806
	(0.602)	(1.667)	(0.739)
High school	-0.177	-0.074	-0.451
	(0.269)	(0.517)	(0.343)
Vocational college	-0.604*	-0.737	-0.139
	(0.342)	(0.618)	(0.364)
College	0.204	-15.822***	0.528
	(0.394)	(0.672)	(0.426)
Male	0.308	1.380***	1.329***
	(0.232)	(0.427)	(0.299)
Married	0.294	0.441	0.626*
	(0.278)	(0.520)	(0.343)
Ln(distance)	-2.981***	-1.656***	-0.322**
	(0.153)	(0.203)	(0.140)
Car owner	0.455	0.686	3.849***
	(0.307)	(0.475)	(0.321)
Electric 2-wheel owner	-0.424	3.636***	0.436
	(0.328)	(0.497)	(0.370)
Rush Hour	-0.541***	-0.27	-0.595***
	(0.174)	(0.268)	(0.196)
Weekend	0.065	0.206	0.403
	(0.348)	(0.730)	(0.346)
Purpose-home	0.593	-0.699	-1.597**
	(0.544)	(0.997)	(0.720)
Purpose-work	0.239	-0.827	-1.836**
	(0.554)	(0.974)	(0.745)
Purpose-business trip	-1.078	-1.1	-1.472*
	(0.777)	(1.311)	(0.841)
Purpose-shopping	0.791	-1.259	-1.626**
	(0.586)	(1.036)	(0.827)
Purpose-eat	3.029**	0.404	1.359

	(1.176)	(1.474)	(1.237)
Purpose-kids school	0.944	0.222	-1.21
	(0.626)	(1.094)	(0.828)
Purpose-entertainment	0.442	-1.612	-2.700***
	(0.709)	(1.360)	(0.886)
Purpose-social	0.789	-1.58	-0.856
	(0.644)	(1.121)	(0.890)
Observations	2,938	2,938	2,938

Notes: Results from estimation of multinomial logit model. All regressions include dummy variables for each urban district.