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SPATIAL PATTERN OF VEHICLE OWNERSHIP BY VINTAGE

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Introduction

This study examines the spatial pattern of older and newer vehicle ownership rates by using aggregated census and non-census data for small geographic units. Although there is considerable research on how overall ownership varies among neighborhoods, there is a paucity of research on how the age composition of personal vehicles varies across space.² While we expect disadvantaged neighborhoods to have fewer and older vehicles, it is important to quantify these phenomena. The spatial pattern and its determinants are critical to answering basic policy questions such as the impact of transportation on accessing economic opportunities, and to estimating large-scale transportation models for urban planning.³ Moreover, the age of car also has broader

1. Paul Ong is a professor at UCLA's School of Public Affairs, and Cheol-Ho Lee is a doctoral student in UCLA's Department of Urban Planning. We are indebted to UCTC (University of California Transportation Center) and the UCLA Lewis Center for partial funding for this project. We alone are responsible for all interpretations and errors.

2. For this paper, the terms vehicle and car are used interchangeably to mean personally owned light vehicles. The preferred term is vehicle, but the term car or automobile is used in parts of the text when the relevant literature cited uses those terms.

3. The latter models are also used for forecasting future trends and simulating the impacts of policies and programs. Southern California Association of Government's travel demand model (SCAG-TDM) is an example of how vehicle data are used in transportation models. For any given originating traffic zone, the number of trips, mode split, time of trip, and travel distance is a function of the number of private vehicles,

societal consequences because of externalities. An older vehicle produces much more pollutants per mile, therefore contributes disproportionately to the mobile emissions (Dill, 2001). For example, a 1985 vehicle tends to generate nearly 38 times more carbon monoxide per mile than a 2001 model (Beydoun and Guldmann, 2006). For individuals and households, vintage is important because older vehicles are less reliable, thus offering less service to their owners.

Our understanding of the economic importance of transportation resources available to individuals and household comes from the research on the impact of car ownership on employment, which finds a positive and significant relationship. Among welfare recipients, having access to a car improves labor-market outcomes (Ong, 1996 and 2002). Other research has produced similar findings for low-income households in general (Raphael and Stoll, 2001; Ong and Miller, 2004). Moreover, having a reliable car is critical (Goldberg, 2001; Blumenberg, 2006). Access to a car, particularly a reliable one, facilitates job search and the commute to work. There are also indirect benefits because having good transportation makes it easier to fulfill household obligations while working. While public transit can help, particularly in areas where the level of service is very high (Ong and Houston, 2002), public transit is a distant second to owning a personal vehicle for most households in most metropolitan areas, which is not surprising since urban spatial patterns are largely predicated on the automobile. Transportation is so critical in the labor market that employers include having access to reliable transportation as a major part of their hiring decision (Goldberg, 2001)

Measuring a person's transportation resources should not be based only on a dichotomous outcome of ownership. Not all vehicles are able to provide the same level of

plus other household and neighborhood factors (Southern California Association of Governments, 2003).

service, and in general, older cars provide less service and have more mechanical problems. Data from the 2001 National Household Travel Survey show a substantial difference in the average annual miles driven for a new car and a 10-year old car, 15,000 versus 9,900 miles. Moreover, after accounting for individual and household characteristics, VMT is inversely related to the age of car after accounting for individual and household characteristics (Kavalec, 1996). The lower service provided by older car is due in part to lower reliability. Data from Consumers Report indicates that a ten-year-old car has at least eight times as many problems as a new car.⁴ The problems among older cars are likely to be very expensive because they involve major components.

Given that the vintage of vehicles influences the effective level of transportation resources available to individuals and households, the rest of this report addresses one aspect of this topic by examining the spatial pattern of ownership of older vehicles in three parts. Part 1 develops the analytical framework, drawing largely on the literature on the determinants of car ownership in general and discusses the data used to estimate the ownership model, and the information comes from the U.S. Bureau of the Census and other sources. Part 2 presents the empirical findings, which are consistent with a priori hypotheses on the role of economic, demographic and other factors. The report concludes with some recommendations.

4. See Consumer Report, 2006. One of the advantages of this data is the large number of responses. The ten-year estimate is based on extrapolation of the published data. The 2001 Consumer Report survey finds that a five-year-old car has four times the number of problems as a new car, and the 2005 survey shows that the differences is four and a half times. The article also presents information on cars up to eight years old in graphic form, and the lines are approximately linear throughout the range. It should be noted that the estimated number of problems in older vehicles is likely to be biased downward because the readers of Consumer Report responding to the survey are likely to have higher than average income and education, and to be more attentive to maintenance.

Part 1: Modeling Ownership

Ideally, a model of the determinants of the ownership of newer and older cars should be based on underlying causal factors. Most current models of ownership use census or survey data (e.g., the National Household Travel Survey) to examine overall ownership rates or odds, and these models provide a guide to the key causal factors. We start with the basic model for car ownership (regardless of age), which is as follow:

(1) $V_i = f(E_i, D_i, N_i)$ for geographic unit i from the 1st to the n^{th} observations
 V_i is the rate of car ownership (e.g., percent of households with at least one car or average number of cars per household). E_i is a vector of economic variables capturing the financial ability to buy and the price of ownership. This includes the average household income (or some other income related variable, such as the percent in poverty), and it is assumed that automobiles are a normal goods but with declining benefits for each additional one. The other economic variable is the price or cost of ownership. Only a few costs are spatially bound. Gas and repair costs either do not vary significantly over space, or shopping for these goods and services is not necessarily localized (because individuals can purchase outside their neighborhood with relatively little or no additional transaction cost because they frequently travel outside for other reasons). On the other hand, insurance premiums are neighborhood specific because insurance companies base a part of their premiums on geographic location. Moreover, the premiums can vary widely even for the same coverage and driving record.

D_i is the vector of demographic characteristics. Larger households tend to have a greater need of a vehicle or more vehicles than smaller households, *ceteris paribus*. Moreover, there are economies of scale within households (car pooling and time sharing

of a vehicle or vehicles) that lower the cost per passenger mile, thus making ownership less costly relative to other forms of transportation (e.g., public transit). Race is also an important demographic characteristic. Although racial differences in ownership have been observed, most analyses do not explicitly incorporate race as a factor (Kavalec, 1996; Dill, 2001). Instead, the racial differences are assumed to be the result of differences in other factors, such as income and family structure.

However, there are good reasons to include race in the model because there is considerable evidence of discrimination in the new car, financial and insurance markets. Audit studies, where testers of two different races are sent to shop for an automobile, show that minorities are given higher quotes for a new vehicle (Ayres and Siegelman, 1995; Riach and Rich, 2002), although there appears to be little or no difference in the final price among those who do purchase (Goldberg, 1996). This may be due to the fact minorities quoted higher prices walk away rather than make a purchase. Among those who do buy, minorities face higher borrowing costs (Consumer Federation of America, 2004). Minority plaintiffs have won settlements in suits against several major financial institutions, including those affiliated with major automobile producers (Henriques, 2001; National Consumer Law Center, 2004; National Consumer Law Center, n.d.). Finally, there are differences in automobile insurance premiums in minority neighborhoods. This is due in part to higher risks in these locations (Harrington and Neihaus, 1998), but African American and poor neighborhoods face higher insurance costs even after controlling for risk (Ong and Stoll, 2006). Regardless of whether the cause is risk or redlining or both, the reality is that higher insurance premiums, along with price

discrimination and higher borrowing costs, create barriers to owning a newer car for minorities, and this may push some into the used car market.

Finally, N_i is the vector of neighborhood-level causal factors. Residents in neighborhoods with a high level of public transit service are more likely to find that mass transit can meet many of their needs, and residents in densely populated areas are less likely to travel far for social, shopping and employment activities (Hess and Ong, 2002). Given the greater alternative provided by public transit and lower demand to travel outside the neighborhood, the *a priori* assumption is that these types of neighborhoods would have lower ownership rates.

Including household income, however, may potentially create an endogeneity problem because earnings (a major component of household income) and vehicle ownership are causally related to each other in both directions (Ong, 2002; Raphael and Rice, 2002). In other words, income is a function of vehicle ownership and other variables:

$$(2) Y_i = y(V_i, X_i) \text{ for geographic unit } i \text{ from } 1 \text{ to } n.$$

Y_i is average household income (or some other income related variable, such as the percent in poverty), V_i is the rate of car ownership (percent of households with at least one car), and X_i is the vector of other factors. Equations (1) and (2) form a system of simultaneous equations, thus estimating only equation (1) would produce biased parameters.

One way to address this potential problem is to replace observed household income in equation (1) with predicted household income constructed from instrumental

variable or variables that are highly correlated with income but not correlated with the stochastic component for equation (1).

$$(3) \hat{y}_i = y(P_i) \text{ for geographic unit } i \text{ from } 1 \text{ to } n,$$

where P_i is a vector of human capital and household characteristics that affects labor market outcomes. Equations (1) then can be rewritten with the instrumental variable as:

$$(4) V_i = f(\hat{y}_i, I_i, D_i, N_i) \text{ for geographic unit } i \text{ from the } 1^{\text{st}} \text{ to the } n^{\text{th}} \text{ observations}$$

Where \hat{y}_i is the predicted household income, and I_i is the insurance cost.

The above model of the determinants of the ownership can be disaggregated into two parts, one for newer cars and the other for older cars. The same variables that influence overall ownership rates or odds should also influence the rates by age of vehicle. The basic models are as follow with the specific independent variables:

$$(5) N_i = g(\hat{y}_i, I_i, H_i, M_i, D_i, T_i) \text{ and}$$

$$(6) O_i = h(\hat{y}_i, I_i, H_i, M_i, D_i, T_i) \text{ for geographic unit } i \text{ from the } 1^{\text{st}} \text{ to the } n^{\text{th}} \text{ observations.}$$

N_i is the average number of new cars per household, and O_i is the average number of older cars per household. \hat{y}_i is predicted average household income, I_i is the average insurance premium, H_i is average household size, M_i is the proportion of the population that is minority, D_i is population density, and T_i is the level of public transit. There is no reason to assume *a priori* that the effects of the independent variables on newer and older cars would be the same, and in fact, the effects should differ. For example, income should make it more likely to purchase a new car than an older car. One analysis found that households with more than \$100,000 in income are about twice more likely to replace an existing car with a new one than those with income of \$30,000 (Kavalec, 1996). The

effect of race is more complicated. We know that there are numerous forms of discrimination in the new car market, as discussed above, which would dampen demand for new cars, thus lower the rate of new car ownership. This can increase the age of the stock of vehicles owned by minorities if discrimination is more extensive in the new car market than in the used car market, or if discrimination delays the timing of trading in.⁵

The mathematical specifications for the ownership models for all vehicles (A_i) and vehicles by vintage (N_i and O_i) are:

$$(7) A_i = \alpha^A + \beta^{A,1}\hat{y}_i + \beta^{A,2}I_i + \beta^{A,3}H_i + \beta^{A,4}M_i + \beta^{A,5}D_i + \beta^{A,6}T_i + \varepsilon_i^A$$

$$(8) N_i = \alpha^N + \beta^{N,1}\hat{y}_i + \beta^{N,2}I_i + \beta^{N,3}H_i + \beta^{N,4}M_i + \beta^{N,5}D_i + \beta^{N,6}T_i + \varepsilon_i^N$$

$$(9) O_i = \alpha^O + \beta^{O,1}\hat{y}_i + \beta^{O,2}I_i + \beta^{O,3}H_i + \beta^{O,4}M_i + \beta^{O,5}D_i + \beta^{O,6}T_i + \varepsilon_i^O$$

Where α 's are constants, β 's are parameters measuring the impact of the causal factors on ownership rates, and ε 's are stochastic terms. Both predicted income (\hat{y}) and insurance premiums (I) are in log form to account for the declining marginal effect of each additional unit. OLS (ordinary least squares) is used to estimate the coefficients. Several sources are used to assemble the data for the variables, and the data cover Los Angeles County.

The dependent variables (average vehicles per household, total and by vintage) are constructed from two data sources reported at the ZIP code level. The number of vehicles comes from the 2000 Census SF-3 (Summary file 3) files and is normalized by number of households. The Census uses ZIP Code Tabulation Areas (ZCTA), which are close but not identical to the ZIP code areas defined by the U.S. Postal Services (USPS).

5. Technically, purchases are a part of the flow of vehicles into the stock of vehicles. If the flow from the used car market is increased relative to the flow from the new car market, then in steady state, the stock would be on the average older. If existing vehicles are kept in the stock longer before being replaced, then the average age of the vehicles should be higher.

Unfortunately, the Census does not collect data on the age of vehicles. We get vintage data from a special tabulation of vehicle registration data from the California Department of Motor Vehicles (DMV) for October 2000, a time period that closely matches the timing of the 2000 Census. The data are only for light vehicles and exclude heavy commercial vehicles. The tabulations are produced by the California Energy Commission (CEC), which has developed a method to differentiate personal and business vehicles. This approach produces the best estimate of the number of registered personal vehicles (Hunstad, 1999), and is used by a number of state agencies for analyses. The tabulation includes two vintage categories, those 10 years and older (1989 or earlier models) and those less than 10 years (1990 or later models). Since the DMV data are based on USPS zip code boundaries, the DMV data are allocated to ZCTAs by using the GIS proportional split method.⁶

Unfortunately the DMV tabulation cannot be directly used to calculate the rate of newer and older because there are large number of unregistered vehicles (as well as uninsured motorists), and the rates for these phenomena varies across neighborhoods. (Hunstad, 1999; California Department of Insurance, Statistical Analysis Division, 2004; California Department of Insurance, n.d) Thus it is not surprising that for the overwhelming majority of the ZIP code areas, there are more vehicles reported in the Census data set than in the DMV data set. (The areas where the opposite is true appear to be due to the limitation of the CEC method to eliminate all business vehicles.) This pattern also leads us to conclude that the Census data set includes many of the unregistered vehicles, thus provides a better count of vehicles per household.

6. There are also data for DMV ZIP code areas with no corresponding ZATC, and these data points are dropped.

We use two different approaches to disaggregate the census data into vintage categories. The first method assumes that the relative proportions by age in stock reported by the Census are the same as the proportions observed in the DMV data. For example, for a given ZIP code area, if 20% of the DMV vehicles are older ones, then we assume that 20% of the Census vehicles are also of the same vintage. This is likely to produce an upward bias in the estimated of the number of newer vehicles because unregistered vehicles are more likely to be old one. The second approach assumes that people register all newer vehicles, thus the DMV counts for newer vehicles are taken as being accurate. Under this assumption, the estimated number of older vehicles is defined as the difference between the Census counts and the number of newer DMV vehicles. (When number of census vehicles is larger than the total number of DMV registered vehicles in a ZCTA, we use the proportionate allocation in the first approach.) This second approach produces a downward bias in the estimated number of newer vehicles because it misses unregistered newer vehicles. The size of this bias is likely to be relatively small because most unregistered vehicles are older ones.

The data for independent variables also come from several sources. Car insurance premiums were collected over the Internet during the summer of 2000 from multiple quotes from multiple insurance companies for each zip code in the city of Los Angeles. Insurance premium estimates were for the liability component only and were provided by the following website: <http://www.realquote.com>. To capture a “pure” geographic variation of insurance rates, we held the characteristic of the “applicant” constant by using the same demographic profile for every ZIP code area.⁷ The insurance premium for

7. A 25-year old, employed single mother, who has been driving for 7 years, has taken a driver training course, has one moving violation, but no accidents, and does not smoke. She owns a 1990 Ford Escort LX,

each zip code is the average of quotes from at least a half dozen companies. The data are also transformed into ZCTA by using the GIS proportional split method.

Household, human-capital and neighborhood characteristics are based on ZCTA data from the 2000 Census SF-3 data set. We include the population density, percentage of Black and Hispanic population, household size, and the median household income of the ZCTA as the main socioeconomic and neighborhood variables. The level of public transit service is measured by bus stop density data, which come from the Southern California Association of Governments (SCAG). The file contains 102,612 bus stops, which are unique by bus stop location and bus lines of multiple transit agencies. The data are normalized by area.

Part 2: Empirical Results

Table 1 presents the descriptive statistics for the dependent and independent variables. There are five dependent variables because of the two alternative methods of estimating the numbers of older and newer vehicles. The variables based on first method (the proportion in the Census data is assumed to be identical to the proportion observed in the DMV data) are denoted as V1, and the variables based on the second method (the number of newer vehicles in the Census data is assumed to be equal to the number of newer vehicles in the DMV data) are denoted by V2. The difference in the relative distribution by vintage between the two methods is noticeable but not very large (59% newer and 41% older for method 1, and 65% newer and 35% older for method 2). There is substantial variation in the insurance premium (because of the log form, 0.01

two-door hatchback with no anti-theft devices, no anti-lock brakes, and no airbags, and parks on the street. She carries only the minimum insurance required (\$15/30,000 bodily liability, \$5,000 property liability) with no deductibles.

represents a 1% difference), and even a larger variation in household income. Like many other metropolitan areas, Los Angeles has a proportionate large minority population.

Table 1. Descriptive Statistics of Key Variables

Variables	Mean	Median	Std Deviation
Total Vehicles per Household	1.639	1.680	0.365
Older Vehicles per Household (V1)	0.574	0.571	0.161
Older Vehicles per Household (V2)	0.678	0.686	0.183
Newer Vehicles per Household (V1)	1.065	1.070	0.336
Newer Vehicles per Household (V2)	0.961	0.969	0.306
Insurance Premium (Log)	6.764	6.743	0.198
Median Household Income (Log)	10.700	10.703	0.437
Predicted Median Household Income (Log)	10.705	10.714	0.429
Bus Stops	0.376	0.302	0.370
Population Density	0.860	0.765	0.678
Household Size	2.998	2.941	0.718
Percent of Blacks	0.091	0.037	0.146
Percent of Hispanics	0.337	0.296	0.243

The estimated OLS models with predicted household income are reported in Table 2.⁸ The models in general do a reasonable job of explaining the cross-sectional variation in the dependent variables, with adjusted R-Squares ranging from .34 to .82. All estimated coefficients have signs that are consistent with the *a priori* assumptions, and most are statistically significant. As expected, areas with higher levels of transit service and with higher population density have lower ownership rates. The effect of public transit is greater on the ownership of older vehicles, which is not surprising since the population that is relatively more likely to rely on older vehicles is more likely to use

8. The estimated OLS models with observed household income are reported in the Appendix, Table A2. As expected, these models have higher adjusted r-squares, but the difference is minor. Comparing the models with and without instrumental variables show that are differences in the estimated coefficients, although many of the differences are small. In the models with observed household income, the coefficients for population density are more likely to be statistically significant.

public transit. Population density has minimal impact, and the only statistically significant coefficient is for the model for newer vehicles using the second method of estimating the number of newer vehicles (direct DMV counts). The negative impact may be due to the problems and cost (risk) of owning and parking a vehicle in such neighborhoods. This may be particularly true for the greater risk of leaving a newer car on public streets. Household size also has the expected impact, that is, larger households tend to have more vehicles, *ceteris paribus*.

**Table 2. Regression Result
(with predicted median household income)**

	Total Vehicles	Older Vehicles (V1)	Newer Vehicles (V1)	Older Vehicles (V2)	Newer Vehicles (V2)
Constant	-0.941	0.910 *	-1.851 **	1.299	-2.240 **
Insurance Premium (Log)	-0.394 ***	-0.190 ***	-0.204 ***	-0.269 ***	-0.124
Predicted Household Income (Log)	0.432 ***	0.058 *	0.374 ***	0.087	0.346 ***
Bus Stops	-0.224 ***	-0.108 ***	-0.116 ***	-0.109 ***	-0.115 ***
Population Density	-0.034	-0.018	-0.016	0.011	-0.045 *
Household Size	0.286 ***	0.080 ***	0.206 ***	0.082 ***	0.205 ***
Percent of Blacks	-0.143	0.229 ***	-0.371 ***	0.184 *	-0.326 ***
Percent of Hispanics	-0.347 ***	0.360 ***	-0.707 ***	0.131	-0.478 ***
Number of Observations	265	265	265	265	265
Adjusted R-square	0.813	0.697	0.819	0.341	0.732

P-value: * p<0.05; ** p<0.01; *** p<0.001

The estimated coefficients on the minority variable reveal an interesting insight into the effects of discrimination vehicle ownership.⁹ Taken alone, the model for total

9. The models were also tested using separate variables for the percent African American and percent Latino. The estimated coefficients have very similar patterns as that for the combined minority population, so the latter form is used.

vehicle ownership suggests that there is no racial impact on Blacks, *ceteris paribus*. The estimated coefficient is negative but statistically insignificant. However, when ownership is disaggregated by vintage, the racial effect becomes clearer: Blacks have fewer newer-vehicles and more older-vehicles, after accounting for other factors. The impact is not insignificant. In a neighborhood that is predominantly Black, there is a net shift of about a half of a vehicle per household across the two vintage categories. This is consistent with the hypothesis that discrimination in the new car market either pushes Blacks into the used car market, delays their replacement of older cars, or both. The impact on Hispanics is even larger, with a net shift of up to a whole vehicle between the two categories. Again, this is consistent with the discrimination hypothesis, although there may also be an effect due to the international remittance among Hispanic immigrants. In other words, they have less disposable income to spend on a vehicle. Regardless of the cause, the consequence is that these residents in minority neighborhoods are left with less reliable vehicles, *ceteris paribus*.

Higher insurance premiums lower vehicle ownership rates, but have a larger negative impact on older vehicles.¹⁰ Because the variable is in log form, the results indicate a decline in the margin impacts at higher level.¹¹ Household income is positively related to vehicle ownership rates, but has a larger positive impact on newer vehicles.

10. The result is based on the second method (V2), where the number of newer vehicles in the Census data is assumed to be equal to the number of newer vehicles in the DMV data. With the other method (V1), higher insurance premiums have a marginally larger negative impact on newer vehicle ownership. This is due perhaps to the way that vintage is imputed to Census data. As mentioned above, it is likely to produce an upward bias in the estimated of the number of newer vehicles.

11. The models were also tested using a linear and a quadratic term for insurance premiums. The results also indicate a decline in the marginal impact (higher premiums lowers ownership but at a declining rate), but the models using this form for insurance premiums have a lower fit as measured the adjusted R-square.

Because the variable is in log form, the results indicate a decline in the margin impacts at higher level.¹²

The effects of the two economic variables are difficult to interpret because of their nonlinear specification. Simulating the rate of ownership over the observed range of the two independent variables provides additional insights into the magnitude of the impacts, and the results of the simulations are depicted in Figures 1 and 2. Higher insurance cost has both a larger absolute and relative impact on the number of older vehicles than on the number of newer vehicles, thus producing a noticeable change in the composition of the stock of vehicles by vintage. The greater impact of household income on owning newer vehicles is visually apparent. There are two interesting patterns: 1) ownership of older vehicles is not limited to lower-income neighborhoods, and 2) the income point at which the average number of newer vehicles outnumbers is relatively low.

12. The models were also tested using a linear and a quadratic term for household income. The results indicate a decline in the marginal impact (higher income increases ownership but at a declining rate), but the models using this form have a lower fit as measured the adjusted R-square.

Chart 1. Simulation of Vehicles per Household by Insurance Premium

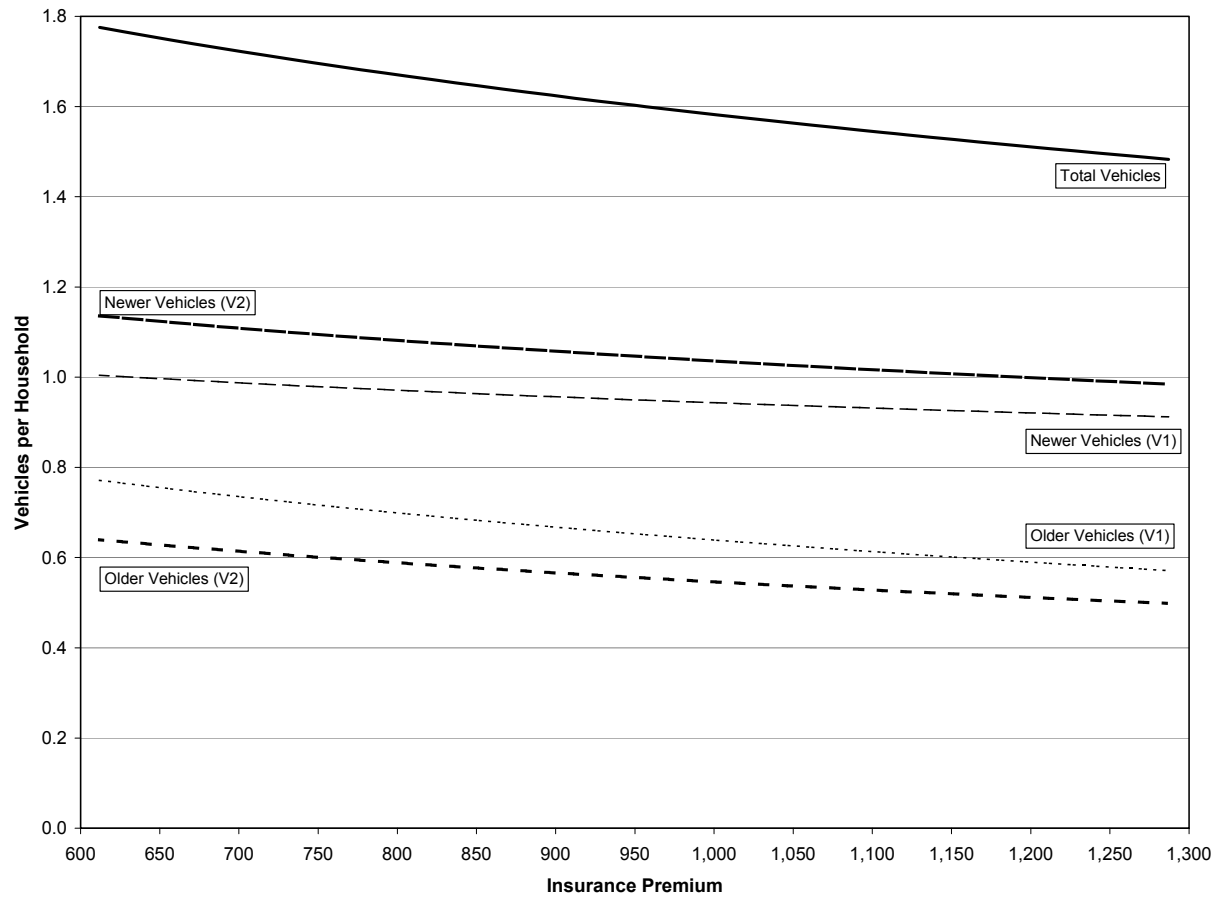
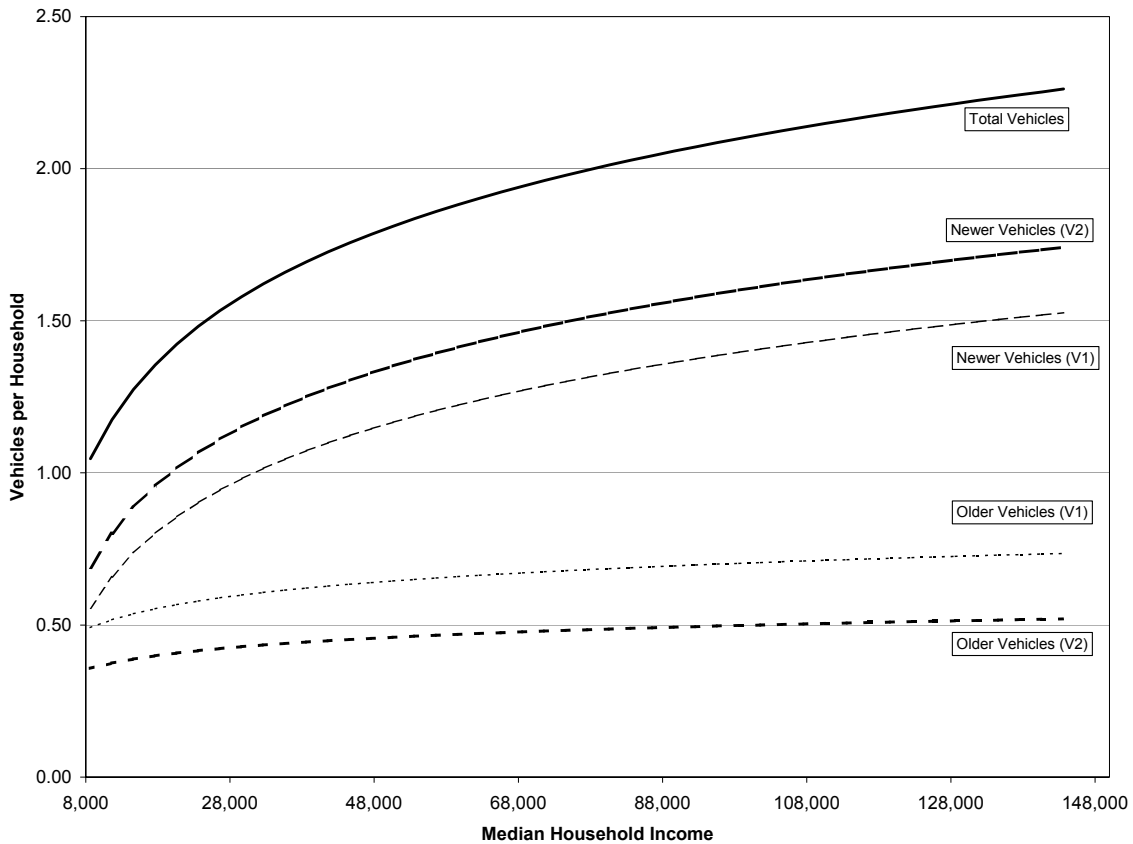


Chart 2. Simulation of Vehicles per Household by Estimated Median Household Income



While the regression results provide estimates of the independent effects of the causal factors, it is worth noting that many of these characteristics overlap in the real world. In statistical terms, this is known as multicollinearity, although the results indicate that there is sufficient variation and sample size to reasonably isolate the independent effects. Nonetheless, it is important from a policy and planning perspective to examine the clustering of neighborhood characteristics. Table 3 presents the average characteristics for four types of neighborhoods: 1) the top quartile in terms of household

income, 2) the bottom quartile in terms of household income, 3) the bottom quartile in terms of insurance premiums, and 4) the top quartile in terms of insurance premiums.

Table 3. Variations by Neighborhood Characteristics
(categorized by observed median household income)

	High Income Neighborhood	Low Income Neighborhood	Low Insurance Premium Neighborhood	High Insurance Premium Neighborhood
Total Vehicles per Household	1.942	1.229	1.898	1.264
Older Vehicles per Household (V1)	0.494	0.576	0.608	0.481
Older Vehicles per Household (V2)	0.662	0.629	0.752	0.569
Newer Vehicles per Household (V1)	1.448	0.653	1.290	0.782
Newer Vehicles per Household (V2)	1.280	0.599	1.146	0.694
Insurance Premium	0.798	1.042	0.687	1.138
Median Household Income Observed	77.624	26.563	59.472	35.469
Median Household Income Estimated	73.053	28.070	58.514	37.653
Bus Stops	0.246	0.645	0.237	0.560
Population Density	0.372	1.502	0.413	1.391
Household Size	2.673	3.329	3.000	2.780
Percent of Black	0.044	0.174	0.044	0.179
Percent of Hispanics	0.110	0.525	0.270	0.357
Number of Observations	67	67	67	67

The data in columns 2 and 4 clearly pick up the impact of income on ownership of newer vehicles. The group of lower income neighborhoods, however, is also affected by having a larger minority population and higher insurance premiums (compared to the group of higher income neighborhoods). The differences by the two groups defined by insurance premiums are shown in the last two columns. The group with the higher cost is also affected by lower income and has relatively more minorities. In other words, disadvantaged neighborhoods tend to be adversely affected by more than one factor.

Part 3: Concluding remarks:

This study demonstrates substantial spatial variations in the ownership of vehicles by vintage, and the findings provide useful policy and planning insights. For example, because of the differences in VMT by age of vehicle, the information can be used to adjust trip generation (particularly distance traveled) by geography in urban transportation models. Perhaps more important are the insights into critical socioeconomic issues, and specifically on how some urban neighborhoods are disadvantaged.

Low-income and minority neighborhoods have both fewer vehicles per household and the vehicles they own are older ones. The negative impacts of limited access to car ownership have been studied, but these studies underestimate the differences because all vehicles are empirically treated as the same. Because older vehicles tend to be less reliable and provide less service, there are additional barriers beyond simple car ownership. One implication of this study is that residents of disadvantaged communities

experience even less access to economic, recreational, and other opportunities in their region because of the spatial variation by vehicle vintage. The findings also points to other potential problems. Because older vehicles tend to pollute substantially more, the spatial distribution means that disadvantaged neighborhoods experience more pollution generated by their own vehicles, and the corresponding adverse health consequences.¹³ Moreover, the spatial pattern means that governmental programs such as scrapping older vehicles to address environmental concerns (Dill, 2001) would have differential impacts across neighborhoods. The findings are also consistent with the literature on racial discrimination in the product market, but go further in uncovering how this affects the type of vehicles owned by minorities.¹⁴

Clearly, this study has limitations but is nonetheless an important step forward. A major problem is the potential endogeneity because vehicle ownership and earned income have dual causality, and this presents a particular problem when using aggregated data. Hopefully, this can be addressed in future research by using an instrumental variable for household income. Some empirical limitations, however, cannot be addressed using existing aggregated data, and future research will require micro-level data.

13. This, however, is only a part of the problem of the unequal distribution of pollutants from mobile sources. Most of the emissions in these neighborhoods are generated from vehicles owned by residents and firms outside the community.

14. We did an additional analysis using the value of vehicles per household (in log form) as the dependent variable. The results are consistent with the analysis on the stock of newer and older vehicles. Household income and household size increase vehicle values, indicating that households spend more on vehicles if they have the financial resources or greater transportation needs because of more household members. Our proxy for the level of public transit and for neighborhood amenities lowers the value, a result consistent with substitution effect. The percentage of Blacks and percentage of Hispanics lower the value, due perhaps to the fact that older cars are more common in minority neighborhoods, *ceteris paribus*. The one independent variable that differs is related to insurance premiums. In the car value model, the coefficient is statistically insignificant, and this may be due to two offsetting effects. One, higher insurance cost has an associated price effect so that a higher price lowers the demand for cars. Two, high insurance premium has a self-selection bias, that is, it forces some households out of the automobile market. Those remaining in the market may treat cars as a luxury good and be more willing to pay high prices.

Reference:

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APPENDIX

Table A1. Median Household Income Estimation Model

	Mean	Std Deviation	Coefficient
Constant			72.4 ***
Percent of High School Degree or Lower	0.449	0.214	23.2 **
Percent of Bachelor's degree or Higher	0.273	0.180	98.9 ***
Percent of Age 25-34	0.161	0.060	-163.9 ***
Percent of Age 55-64	0.080	0.030	-153.6 ***
Percent of Female householder, no husband present	0.194	0.077	-75.0 ***
Percent of Recent Immigrant	0.110	0.074	-75.1 ***
Number of Observations	277		
Adjusted R-square			0.835

P-value: * p<0.05; ** p<0.01; *** p<0.001

**Table A2. Regression Result
(with observed median Household income)**

	Total Vehicles	Older Vehicles (V1)	Newer Vehicles (V1)	Older Vehicles (V2)	Newer Vehicles (V2)
Constant	-2.347 ***	1.327 ***	-3.673 ***	1.316 *	-3.663 ***
Insurance Premium (Log)	-0.329 ***	-0.188 ***	-0.141 **	-0.260 ***	-0.069
Median Household Income Observed (Log)	0.532 ***	0.020	0.512 ***	0.081 *	0.451 ***
Bus Stops	-0.148 ***	-0.112 ***	-0.036	-0.101 ***	-0.047
Population Density	-0.058 ***	-0.028 *	-0.030 *	0.003	-0.061 ***
Household Size	0.229 ***	0.082 ***	0.148 ***	0.075 **	0.154 ***
Percent of Blacks	-0.013	0.204 ***	-0.217 ***	0.189 *	-0.202 **
Percent of Hispanics	-0.181 *	0.320 ***	-0.501 ***	0.133	-0.314 ***
Number of Observations	265	265	265	265	265
Adjusted R-square	0.881	0.693	0.905	0.344	0.808

P-value: * p<0.05; ** p<0.01; *** p<0.001