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LOCATION EFFICIENCY: NEIGHBORHOOD AND SOCIO-ECONOMIC CHARACTERISTICS DETERMINE AUTO OWNERSHIP AND USE – STUDIES IN CHICAGO, LOS ANGELES AND SAN FRANCISCO*

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Auto ownership and mileage per car are shown to vary in a systematic and predictable fashion in response to neighborhood urban design and socio-economic characteristics in the Chicago, Los Angeles, and San Francisco regions. In all three cases, average auto ownership is primarily a function of the neighborhood's residential density, average per capita income, average family size and the availability of public transit. Similarly, the average annual distance driven per car is a strong function of density, income, household size and public transit, and a weaker function of the pedestrian and bicycle friendliness of the community. The similarity of these relationships among the three metro areas, despite their differences in geography and age, suggests that similar relationships may be consistent throughout the United States or worldwide. The application of the results to other metro areas is discussed. The dependence of driving on the policy-related variables of residential density, transit access, and pedestrian and bicycle-friendliness may provide policy makers with additional tools for reducing the costs and environmental impacts of transportation.

Keywords: Location efficiency; Vehicle miles traveled

*The data for the three metropolitan areas are avaliable at www.cnt.org/lem/lemdata.html

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The need to understand auto use is crucial to several areas of public policy. The decision to drive has major effects on household budgets, national and world energy consumption, and the regional and global environment. The impacts of driving can be seen in the construction of highways, increased auto congestion, deterioration of air and water quality, loss of natural habitat and species, and loss of productivity as a result of long commutes, heavy traffic and stress.

There has been a long-running debate, particularly in the U.S., between advocates of "new urbanism" who argue that compact, transit-oriented "traditional cities" allow reductions in driving and associated environmental and economic impacts; and proponents of the view that driving is determined primarily by economic factors such as income and the price of transportation. Some studies have suggested that low density and auto-oriented development reduce accessibility and require longer trips, and, along with poor public transit, high income and large families, lead to higher auto ownership and use. The multiplicity of variables, including regional location and cultural factors, and lack of adequate neighborhood-level data has frustrated definitive analysis of these impacts. This location efficiency research attempts to add quantifiable depth toward resolving the debate.

RECENT STUDIES OF URBAN DESIGN AND DRIVING

In a survey of 32 major cities around the world, Peter Newman and Jeffrey Kenworthy found that the residents of American cities consumed nearly twice as much gasoline per capita as Australians, nearly four times as much as the more compact European cities and ten times that of three compact westernized Asian cities, Hong Kong, Singapore and Tokyo [1]. Gasoline use varied as a function of density both within the subset of American cities and worldwide.

Lacking direct measures of auto mileage, Newman and Kenworthy used motor vehicle fuel consumption. Since motorists often fuel up outside their neighborhoods, fuel consumption may be an adequate indication of regionwide driving but not of individual neighborhoods. Consequently, Newman and Kenworthy were limited to comparing whole metropolitan areas, or, somewhat less confidently, the central cities with their suburbs. Their data suggest that driving is reduced

30% every time density doubles [2]. This implies that even sprawling suburban areas would benefit from only a modest increase in density. For instance, only 15 acres of three to five story limited-parking condos or apartment houses with ground-floor markets (about 100 households/residential acre) replacing parking lots or other underused land along major streets about doubles the density of a sprawling 500 acre neighborhood (3 households/residential acre), cutting average household mileage 30%. If this relationship holds up to the density of Manhattan, with a reduction in driving of 30% every time density doubles, Manhattan families would drive only 8%, or 1/12, as much as nearby suburbanites.

More helpful are studies that directly measure vehicle miles traveled (VMT), like travel surveys where household residents log each trip rather than relying on gasoline consumption. Unfortunately the cost of such surveys limits their size to too few households to provide confidence in the statistical accuracy at neighborhood level. Yet, some general conclusions can be reached. Newman and Kenworthy reported results of a travel survey of United Kingdom cities, which give a 25% reduction in per capita VMT as density is doubled. Similarly, a travel survey in the Greater Toronto Area suggested that doubling the density results in a decrease in per capita VMT of about 25% [3].

A comparison of cities in Washington state found housing density, population density, jobs-housing balance and retail-housing balance to co-vary and to be associated with reduced driving [4].

The above studies were for much larger areas than neighborhoods. Direct comparison of neighborhoods is necessary to determine if neighborhood characteristics like density, transit service and pedestrian and bicycle friendliness – characteristics that can be influenced by public policy – truly influence auto ownership and driving. A 1990 study analyzed these effects with neighborhood-scale data. Actual odometer readings were used to evaluate five communities in the San Francisco region, which were chosen to cover the full range from traditional to suburban [5]. They ranged from 100 household/residential acre northeast San Francisco (Nob, Russian and Telegraph Hills, Chinatown and North Beach) to low density suburban San Ramon, at three households/residential acre.

This study found that high residential density, nearby shopping, good transit and a good walking environment go together, while low density zones usually lacked nearby shopping, good transit and a good walking environment. The co-variance of all these variables increases the difficulty of disentangling their effects, but does allow density to capture much of the effects of the others. Odometer readings recorded when auto owners took their cars in for smog-checks were used to calculate VMT. The study found that residents of higher density communities drive less: 20–30% per household as neighborhood density doubles. Comparing the extremes, the Nob Hill area was found to have 32 times higher household density, much better public transit and 200 times more local shopping (retail and service employees per acre) than San Ramon, while only about one-fourth the household auto ownership and VMT.

Using a household travel study in the Seattle area, Frank and Pivo found that employment density, population density, land-use mix and jobs-housing balance are associated with less auto use [6]. These relationships held up even when household demographics, car ownership and transit are controlled.

The Natural Resources Defense Council (NRDC) followed up Holtzclaw's 1991 study with a study of 27 neighborhoods that ranged from 1.8 households/residential acre to 100 in San Francisco, Los Angeles, San Diego and Sacramento [7]. This study found similar results to the 1991 study; the 27 neighborhoods showing statistically significant reductions in driving associated with high residential density and the quality of transit service. Doubling residential density was shown to lower auto ownership and VMT 16%, while doubling public transit service reduced VMT an additional 5%.

With density as a surrogate for all the variables (including transit, which correlates with density), doubling residential density cut VMT 20%. The other variables, local shopping and pedestrian friendliness, acted in the predicted direction but with less force, and were not statistically significant within the small data base. In both of these NRDC studies the zones were selected to have relatively small variations between average incomes and family size, so income, stage of life and family size were not analyzed statistically. The size and location of these studies limit their generalizability to all neighborhoods and to metropolitan areas outside California.

These relationships are necessarily tested at the neighborhood level. The difficulty of developing the appropriate data for a large number of neighborhoods has driven analysts to using whole metro areas. Gordon and Richardson, for instance, used whole urbanized areas that mixed high density central business districts with sprawling suburbs so that New York had about the same density as Los Angeles [8]. They used census measures of commute trips, which are only 15–25% of the total trips, as the measure of driving. The National Personal Transportation Survey (NPTS) data is insufficient in number of respondents to allow analysis by individual metropolitan area with statistical accuracy, let alone to evaluate trips by zone within the metro area against the zone's density and transit service. Consequently, they group the data into five sizes of metro area: under 1/4 million, 1/4 –1/2, 1/2–1, 1–3, and over 3 million. They then evaluated the differences in trips for those within the central cities (combining dense New York and Chicago with sprawling Houston and Los Angeles), and those outside.

Three studies analyze some of the variables of interest at the neighborhood level. Kara Kockelman, in a study of over 1000 travel analysis zones and 1,200 census tracts in the San Francisco Bay Area, found that the following influence household VMT: household size, auto ownership, income, weighted jobs within 30 min, dissimilarity of the zone's major land use from its neighbors, and the balance of land uses within the zone within a half mile [9]. Kockelman further found that the following influence household auto ownership: household size, income, weighted jobs within 30 min, dissimilarity of the zone's major land use from its neighbors' the balance of land uses within the zone, and population density (persons/square mile).

Using the 1990 NPTS data, Robert Dunphy and Kimberly Fisher reported on the average VMT of the respondents, aggregating together households from around the country whose ZIP codes had the same population density [10]. The nature of the NPTS data handicap its use for analysis of density, transit and other neighborhood impacts on vehicle availability and VMT. For instance, a direct comparison showed households/residential acre to have much more impact than population density at the ZIP code [7]. Five of the 13 NPTS aggregates, which ranged from 50 persons/square mile to 50,000 plus, lived in rural or semi-rural areas, with densities of less than 1000 persons/square mile. The measure of transit, existence of a public transit stop within 3 blocks of the residence, leaves unasked the number of transit lines or frequency of transit service. It equates one bus an hour with five high-frequency subway and 10 bus lines. Moreover, the survey respondents estimated their own annual mileage, wherein drivers experiencing more congested urban traffic might overestimate their mileage.

Despite these data problems, analysis of Dunphy and Fisher's Table 4 shows a decrease of 21% in daily driving as density doubles across the whole density range. For the five ranges above 4000 persons/square mile (about 4 households/residential acre) the decrease is 38% in daily driving as density doubles, explaining 86% of the variance. Paul Schimek further analyzed NPTS data assuming linear or logarithmic impacts of each of the variables, with no explanation of why these forms were used even though a previous (unpublished) study found that density and transit service raised to a power (power function) to have greater explanatory power [7]. Nor were threshold impacts tested. Despite these analytical simplifications and data shortcomings, Schimek found that increasing density and transit reduced vehicle ownership and VMT, however less so than increasing household income and size [11].

None of the above studies analyzed whether severely limited parking discourages auto ownership. This variable's impact is difficult to measure because of the lack of detailed zonal data on parking supply. However the number of parking spaces per capita or per household is inversely related to residential density because most denser areas were laid out with narrow streets and limited parking prior to the 1930s zoning changes which require a generous supply of parking. In addition, the land required by on-site parking usually reduces the density. Cook *et al.* found that the same 3-story apartment house's density varied from 28 units/acre to 64 due only to differences in parking requirements of existing zoning laws [12]. Consequently, to some extent density captures parking tightness.

LOCATION EFFICIENCY STUDY

Our location efficiency study explores the hypothesis that the average household's auto ownership and driving decrease measurably as likely trip destinations become more convenient, especially by non-automotive modes. Further, it tests the assumptions that residential density, center proximity, local shopping, public transit accessibility and the pedestrian and bicycle friendliness of the neighborhood are good measures of that convenience.

Why these variables? Density is a measure of the number of nearby destinations. The higher the density, the more nearby destinations and the shorter the trips. Residential density, the number of households per residential acre, seems to be the best measure because it focuses on the developed area and is not diluted by farmland or parks within the zone but outside the urban area. But other measures of density are also tested. Center proximity is a measure of the neighborhood's access to concentrations of jobs and shopping. Local shopping is a measure of the number of restaurants, markets, retail stores, insurance agents, and of course video rental stores, nearby. Public transit is important as an alternative to driving. A high pedestrian and bicycle friendliness indicates how attractive the areas are to these alternatives to driving. These variables are correlated; high density neighborhoods tend to have local shopping, good public transit, sidewalks, slow vehicle speeds, and to be located near job centers.

This location efficiency study seeks to further quantify the statistical relationship of such locational variables to auto ownership and driving to facilitate development of the Location Efficient Mortgage^{SM} (LEM), as well as help measure the costs and benefits of alternative development patterns. The LEM would allow a household to buy a more expensive home in a location efficient area by committing their auto savings to repaying the mortgage, interest, taxes and insurance. This study also seeks to separate the influence of household income and size from the locational variables.

The study collected data for the Chicago Area Transportation Study's 316 Dram-Empal zones covering the Chicago metropolitan area, the Southern California Association of Governments' 1700 Travel Analysis Zones covering the Los Angeles metropolitan area and the Metropolitan Transportation Commission's 1099 Travel Analysis Zones in the San Francisco metropolitan area. Zones comprised primarily or wholly of parks, military bases, prisons, airports or industrial facilities are non-residential and were eliminated from the data base, leaving 314, 1459 and 1047 zones, respectively.

Models are developed to predict *auto ownership* per household and *vehicle miles traveled* (VMT). Average vehicles available for each zone is from the 1990 U.S. Census data. VMT per vehicle is derived from 1990 to 1995 odometer readings recorded when owners take their vehicles in for emission systems inspections (biennial smog checks) in California and Illinois. The vehicles were assigned to zone using the ZIP code of the owner or lessor after eliminating auto rental and cab fleets. The raw miles/year averages for newer cars (first inspection at 2 years old) and older cars (between two inspections) were weighted to reflect the percentage of both groups of cars in the total fleet.

Zonal average VMT per household is assumed to be the zone's average VMT per vehicle times the average number of vehicles per household. Figures 1 to 3 show the zonal average VMT/Hh for Chicago, Los Angeles and San Francisco.

The dependent variables were fit to a range of potential explanatory variables, including the socio-economic factors of average income per household and per capita, and average household size. Locational variables tested were: density, transit service and access to jobs by transit, availability of local shopping , pedestrian and bicycle friendliness, and proximity to jobs.

The *density* measures tested were households/residential acre, population/acre and population/residential acre. The data were compiled from the census and regional planning organizations. Household and per capita *income* ($/Hh, $/P) and *household size* (P/Hh) were derived from 1990 census data. Total acreage includes residential, commercial, industrial, agricultural, parks and open space, and any other categories used.

The measure of *transit* accessibility is the zonal transit density (Tr), which is the daily average number of buses or trains per hour times the fraction of the zone within 1/4 mi of each bus stop (or 1/2 mi of each rail or ferry stop or station), summed for all transit routes in or near the zone. There may be some double counting where stops are less than 1/4 mi apart, but correcting for this would not substantially alter the order of the TAZs nor the relative differences between zones. Therefore this measure provides a robust assessment of transit service.

An alternative measure, the zonal transit density times the number of jobs reached within 30 min by transit, including average walk, wait,

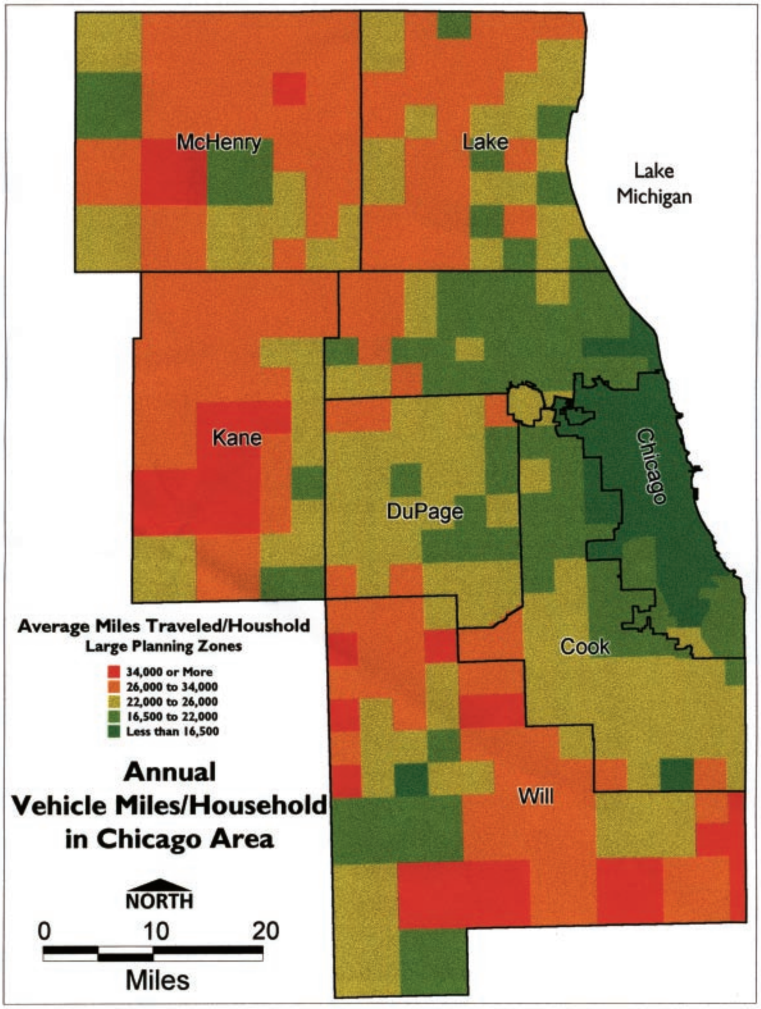

FIGURE 1 Average zonal Vehicle Miles Traveled/Household for the Chicago metropolitan area.

riding and walk times, and any transfer waiting times (TrJ), was tested. It provided no better correlation with auto ownership or driving than the zonal transit density alone. So the simpler zonal transit density is reported. Routes, schedules and stop locations are from the transit

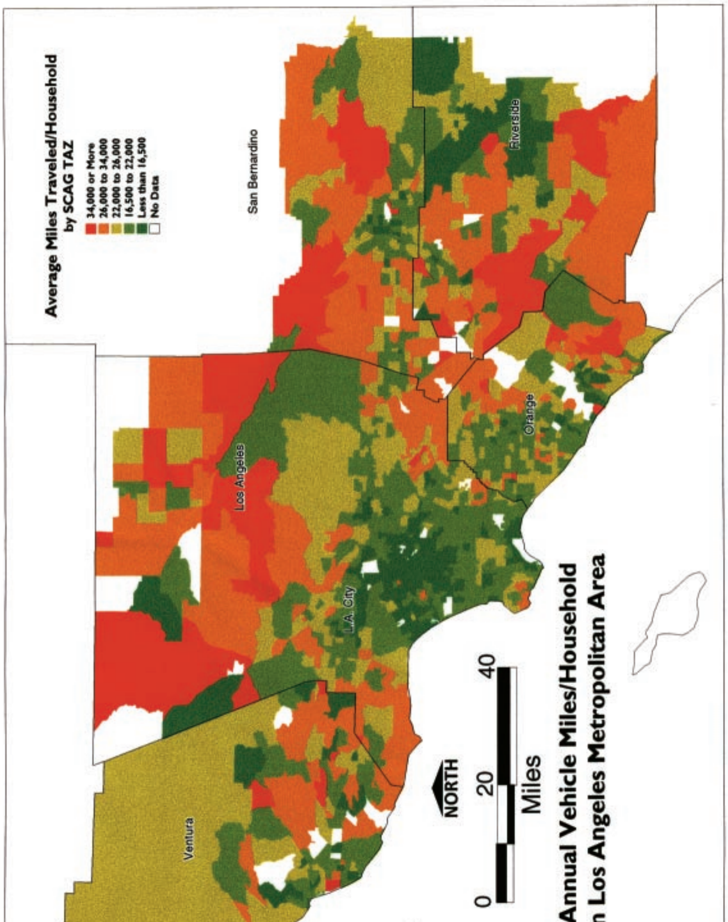

FIGURE 2 Average zonal Vehicle Miles Traveled/Household for the Los Angeles metropolitan area.

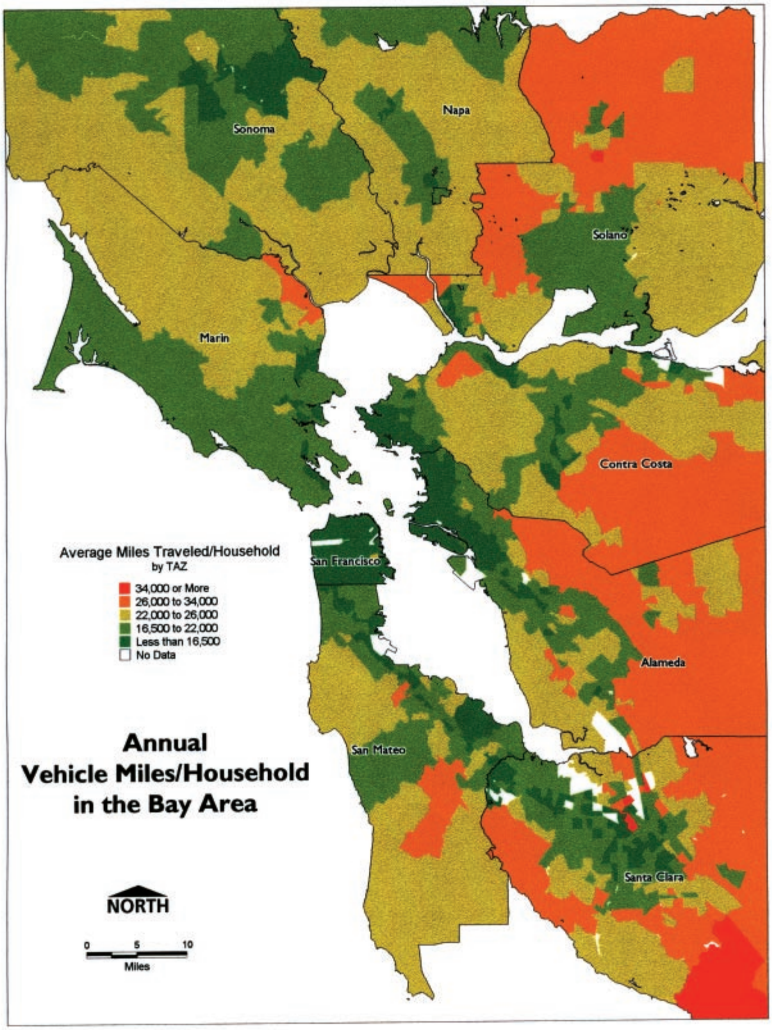

FIGURE 3 Average zonal Vehicle Miles Traveled/Household for the San Francisco metropolitan area.

agencies or the metropolitan planning organizations, who also calculated the number of jobs accessible by transit.

The measure of *center proximity* (CP) is the number of jobs within a 30 min drive, calculated by the Metropolitan Transportation

Commission using their regional transportation model to calculate the average peak-hour drive times between zones for the San Francisco region. An alternative measure is the number of jobs within a 15 min drive divided by the number of jobs within a 30 min drive (E15/E30). This provides a measure of the relative availability of jobs locally. Including CP in the VMT/vehicle analysis provided a marginally higher R^2, but was available only in San Francisco and therefore not included in the general analysis. E15/E30 did not improve R^2 as much as CP did.

Local shopping (Sh) is the number of service and retail jobs per developed area within the zone, from the U.S. Census. Zones with centroids less than 1/4 mi apart were combined for this calculation.

The measure of *pedestrian/bicycle friendliness* (Ped) is the number of census blocks per hectare (street grid), plus an adder based upon the mean year the housing was built, both from the U.S. Census, with bonuses for traffic calming, good pedestrian conditions, bike lanes, paths, and bike parking, whether as part of the initial design or added later [13].

Pedestrian/Bicycle Friendliness = *Street Grid* + *Year Built* + *Bonuses*.
Street Grid = (# of census blocks)/(developed hectares).
Year Built = 0.7 if the median year built is 1939, or earlier according to the census; 0.6 if built 1940–42; 0.5 if 1943–45; 0.4 if 1946–48; 0.3 if 1949–50; 0.2 if 1951–52; 0.1 if 1953–55; 0 if 1956 or newer.
Bonuses: traffic calming credit up to 1.0, and bike credits up to 0.5.

A fine street grid shortens routes and offers more alternatives, and its frequent intersections slow traffic. The measure works because older neighborhoods tend to have a fine street grid, sidewalks, narrow streets, slower traffic and buildings closer to the sidewalk.

We also tested socioeconomic variables available at the zonal level: average *household* size, average *household income* and average *per capita income*. However, we were not able to explore any independent impact of neighborhood parking supply or cost.

ANALYSIS OF AUTO OWNERSHIP AND DRIVING

For the statistical analysis the dependent variables were weighted [14] to compensate for uncertainties in sampling. The means and standard deviations of each of the independent and dependent variables are given in Table I. The correlation of each of the independent variables (locational and socio-economic) with auto ownership and VMT was tested. In the San Francisco area, for instance, Hh/RA correlated with 63% of the variation in Veh/Hh, followed by transit-job access at 55%, Hh/TA at 52%, transit service at 49%, income/household at 43%, shopping at 35% and household size at 28%.

In the three metropolitan areas, the variable that correlated most strongly with Veh/Hh and VMT/Hh was Hh/RA (Table II). Figures 4 and 5 show that there is a very strong relationship of residential density to auto ownership and driving in all three regions studied, even before evaluating the other variables – income, household size, transit service, pedestrian/bicycle friendliness, etc. The strength of this correlation supports the hypothesis that increasing residential density increases the number of desirable nearby destinations and accessibility to public transit, while reducing parking.

When tested against each other, many of the independent variables prove to be highly correlated. This complicates the analysis by making it harder to pick apart the separate influences of density, transit, local shopping, center proximity and pedestrian/bicycle friendliness. Essentially this means that to some extent density captures the effects of local shopping, transit and pedestrian and bicycle friendliness.

Bounded power fits ($y = A[(x + B)/(X_{avg} + B)]^{-C}$) gave the strongest single-independent-variable correlations. The differences between the calibration values reflect the city-to-city differences in weather, terrain, culture, layout, etc. These correlations show that in Chicago, *each* doubling in residential density above the threshold level reduces household auto ownership by approximately 33% and VMT by 32%; in Los Angeles by 35% and 35%; and in San Francisco by 40% and 43%.

As much as possible, we based the forms of our fits on simple modeling of the physical situations. For instance, since doubling density doubles the number of nearby destinations, and doubling transit service doubles the number of destinations you can easily reach, it is reasonable to expect that for both each doubling would decrease auto ownership and VMT by a similar percentage – a log–log or power fit. However, there are limitations on how many cars a household can own, and how many miles even the most auto-entranced

TABLE I Summary Statistics

	San Francisco				Los Angeles				Chicago			
	Mean	*Sigma*	*Max*	*Min*	*Mean*	*Sigma*	*Max*	*Min*	*Mean*	*Sigma*	*Max*	*Min*
Hh/Res Acre	9.884	20.45	467	0.3504	7.140	7.234	76.95	0.01209	4.981	9.809	106.0	0.321
Hh/TotAc	4.980	7.073	72.61	0.003329	3.544	3.524	32.584	9.84E-06	1.885	3.123	22.48	0.00869
Pop/Res Acre	24.33	38.95	781.3	1.504	21.23	21.95	267.8	0.01209	14.39	25.97	315.0	0.791
Pop/Tot Acre	12.38	14.74	145.0	0.008493	10.49	10.11	78.762	9.84E-06	5.200	7.684	51.108	0.058
TotAc/ResAc	10.34	43.99	638.0	1	15.46	68.98	1228	1.0474	6.305	9.104	80.714	1.243
Cen Prox	0.5499	0.3014	1.1584	0.001429	0.3125	0.2531	1.000	7.54E-06	–	–	–	–
Emp 15/Emp 30	0.2112	0.1095	1	0.007452	–	–	–	–	–	–	–	–
Local Shopping	4.972	17.06	249.3	0	3.603	7.226	137.6	0	–	–	–	–
Zon Tr Den	22.66	65.53	814.64	0	6.132	41.22	865.5	0	18.29	145.0	2477	0.000
Tr Job-Acc	6.149	29.631	393.862	0.0	4.182	32.68	523.0	0	–	–	–	–
Ped/Bike Fr	0.500	0.430	2.200	0.00213	0.2332	0.1640	2.094	0.004398	0.2066	0.2681	1.185	0.0156
Pop/Hh	2.728	0.5961	5.862	1.297	3.032	0.667	5.953	1	2.916	0.3548	5.525	1.681
Hh Inc	52818	23802	197526	7500	39144	17376	143046	5776	45225	13439	118882	13456
$/cap	20128	9583	71239	3194	13784	7138.78	48562.4	1983	15651	4660	42563	3968
Weighted Means												
Veh/Hh	1.770	0.4961	4	0.0826	1.771	0.5240	5.460	0.100	1.473	0.400	2.579	0.4584
VMT/Veh	10184	983	13819	7707	11007	1117	14799	8462	11759	1105	16766	9756
VMT/Hh	17161	5987	42581	875.2	18944	6938	66318	1141	16997	5896	35364	6136

TABLE II The best single variable equations to predict Veh/Hh and VMT/Hh. Veh/Hh is Vehicles/Household, VMT/Hh is Vehicle Miles Traveled/Household, and Hh/RA is Households/Residential Acre. Percent of variance explained and the degrees of freedom

	R^2	*Degrees of freedom*
Chicago		
$\frac{\text{Veh}}{\text{Hh}} = 1.664\left(\frac{5.287 + \text{Hh/RA}}{5.287 + 4.981}\right)^{-0.581}$	84.9%	312
$\frac{\text{VMT}}{\text{Hh}} = 19475\left(\frac{3.412 + \text{Hh/RA}}{3.412 + 4.981}\right)^{-0.555}$	86.3%	312
Los Angeles		
$\frac{\text{VeH}}{\text{Hh}} = 1.813\left(\frac{7.930 + \text{Hh/RA}}{7.930 + 7.140}\right)^{-0.622}$	56.5%	1457
$\frac{\text{VMT}}{\text{Hh}} = 19749\left(\frac{4.814 + \text{Hh/RA}}{4.814 + 7.140}\right)^{-0.639}$	62.7%	1457
San Francisco		
$\frac{\text{Veh}}{\text{Hh}} = 1.650\left(\frac{11.297 + \text{Hh/RA}}{11.297 + 9.884}\right)^{-0.739}$	63.3%	1045
$\frac{\text{VMT}}{\text{Hh}} = 16476\left(\frac{9.548 + \text{Hh/RA}}{9.548 + 9.884}\right)^{-0.817}$	62.5%	1045

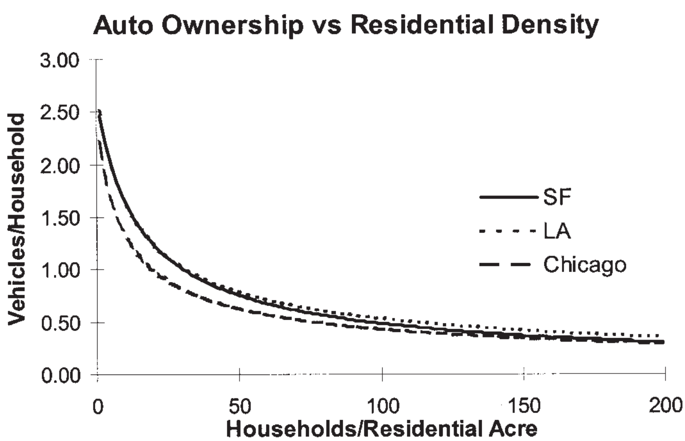

FIGURE 4 The reduction in vehicles per household as residential density increases.

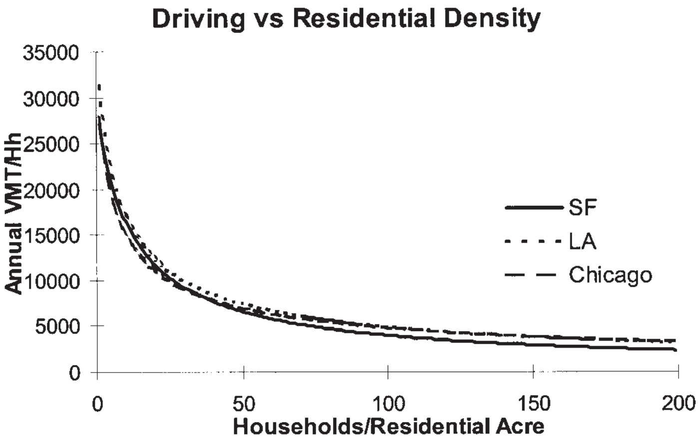

FIGURE 5 The reduction in vehicle miles traveled per household as residential density increases.

folk can drive, therefore we modified the power fit form to be bounded as the density goes to zero. Similarly, since more people in the household increase the number of drivers and people to be driven around, we expected a linear relationship of household size with autos and VMT. However, we had less reason to anticipate a particular mathematical form (linear, power, bounded power, root, polynomial, exponential, etc.) for the relationship between income or pedestrian/bicycle friendliness and auto ownership or VMT. So we tested various mathematically simple forms that had appropriate behavior over the ranges of the independent variables. We derived the forms of the equations using the San Francisco data and then used these forms to derive the equations for the other two regions.

Using the data available in all three geographical regions and the same equation forms, the variables which consistently explain the most variance in vehicles/household (Veh/Hh) are net residential density (Hh/RA), per capita income ($/P), household size (P/H) and transit accessibility (Tr). For vehicle miles traveled/vehicle (VMT/Veh) the best variables are total residential density (Hh/TA), P/H, pedestrian/bicycle friendliness (Ped) and $/P (Table III). Households/residential acre (Hh/RA) had the strongest correlation to vehicle ownership, while households/total acre (Hh/TA) had the strongest correlation to

TABLE III The best equations to predict Veh/Hh, VMT/Veh and VMT/Hh in all three regions. H/RA is Households/Residential Acres, H/TA is Households/Total Acre, $/P is Income/Capita, P/H is Persons/Hh, Tr is Zonal Transit Density, Ped is Ped/Bicycle Friendliness surrogate, exp(x) is e^x and $\sqrt{\text{Ped}}$ is the square root of the Ped/Bicycle Friendliness surrogate. The degrees of freedom are the same as in Table II

	R^2
Chicago	
$\frac{\text{Veh}}{\text{Hh}} = 1.902\left(9.955 + \frac{\text{H}}{\text{RA}}\right)^{-0.2797}\left(1 - e^{-(0.000142(\$/\text{P}))^{1.2915}}\right) \times \left(1 + 0.4893\frac{\text{P}}{\text{H}}\right)(\text{Tr} + 2.960)^{-0.0685}$	96.3%
$\frac{\text{VMT}}{\text{Veh}} = 11620\left(0.1662 + \frac{\text{H}}{\text{TA}}\right)^{-0.0547}\left(1 + 0.00653\frac{\text{P}}{\text{H}}\right) \times \left(1 - 0.0249\sqrt{\text{Ped}}\right) - 0.0818\left(\frac{\$}{\text{P}} - 22136\right)$	46.8%
$\frac{\text{VMT}}{\text{Hh}} = \frac{\text{Veh}}{\text{Hh}} \times \frac{\text{VMT}}{\text{Veh}}$	93.5%
Los Angeles	
$\frac{\text{Veh}}{\text{Hh}} = 1.732\left(6.155 + \frac{\text{H}}{\text{RA}}\right)^{-0.0925}\left(1 - e^{-(0.000131(\$/\text{P}))^{0.8278}}\right) \times \left(1 + 0.7936\frac{\text{P}}{\text{H}}\right)(\text{Tr} + 30.796)^{-0.1865}$	78.6%
$\frac{\text{VMT}}{\text{Veh}} = 11624\left(0.3432 + \frac{\text{H}}{\text{TA}}\right)^{-0.0681}\left(1 + 0.01555\frac{\text{P}}{\text{H}}\right) \times \left(1 - 0.1078\sqrt{\text{Ped}}\right) - 0.04095\left(\frac{\$}{\text{P}} - 22136\right)$	42.0%
$\frac{\text{VMT}}{\text{Hh}} = \frac{\text{Veh}}{\text{Hh}} \times \frac{\text{VMT}}{\text{Veh}}$	80.0%
San Francisco	
$\frac{\text{Veh}}{\text{Hh}} = 4.722\left(22.520 + \frac{\text{H}}{\text{RA}}\right)^{-0.3471}\left(1 - e^{-(0.000112(\$/\text{P}))^{1.2386}}\right) \times \left(1 + 1.0519\frac{\text{P}}{\text{H}}\right)(\text{Tr} + 60.312)^{-0.2336}$	90.2%
$\frac{\text{VMT}}{\text{Veh}} = 10386\left(0.5041 + \frac{\text{H}}{\text{TA}}\right)^{-0.0419}\left(1 + 0.02759\frac{\text{P}}{\text{H}}\right) \times \left(1 - 0.0704\sqrt{\text{Ped}}\right) - 0.01743\left(\frac{\$}{\text{P}} - 22136\right)$	43.8%
$\frac{\text{VMT}}{\text{Hh}} = \frac{\text{Veh}}{\text{Hh}} \times \frac{\text{VMT}}{\text{Veh}}$	87.1%

VMT/vehicle. Local shopping is strongly correlated with density and transit, and did not add to the R^2 after they were taken into account.

Figure 6 shows the impact of residential density and transit on VMT/Hh using the equation for the San Francisco area. Figure 7 shows the sensitivity of annual VMT/Hh to changes in each independent variable with all the others held at their regional average value.

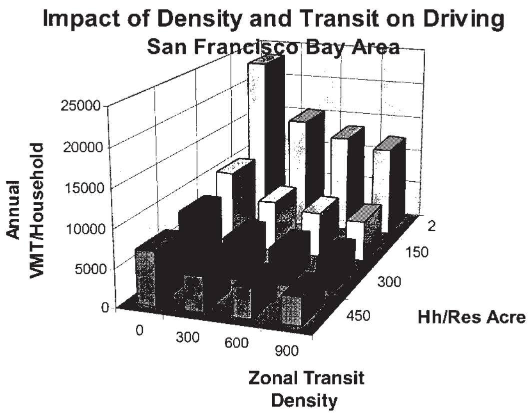

FIGURE 6 The predicted impact of households per residential acre and public transit density on vehicle miles traveled per household.

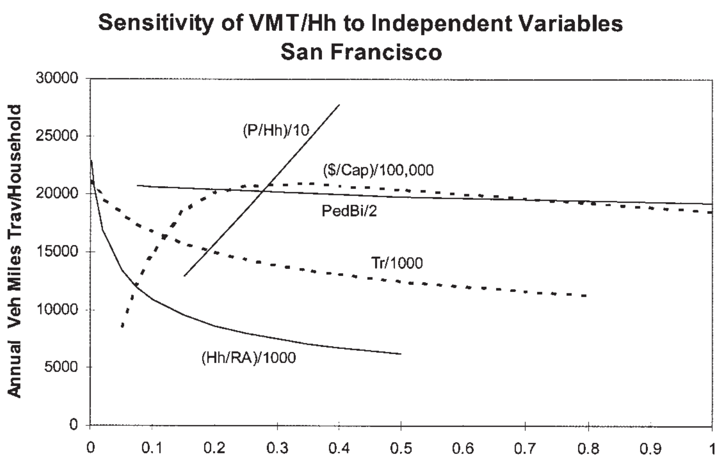

FIGURE 7 Sensitivity of Annual Vehicle Miles Traveled/Household to changes in each independent variable with all the other held at their regional average value, using equations for the San Francisco metropolitan area.

In both the Veh/Hh and VMT/Veh models, density is raised to a negative power, so doubling density causes a fixed decrease in Veh or VMT. In the Veh/Hh model, transit service is raised to a negative power, so doubling Tr causes a fixed decrease in Veh. Household size acts as expected, each additional person adds a fixed increase in Veh or VMT. Improvements in pedestrian and bicycle friendliness reduce VMT/Veh, but with the square root of Ped. The impact of per capita income is a little less straight-forward. It increases with ownership by declining increments as income increases. But VMT/Veh decreases as income increases. The result is that up to an annual income of $25,000 to 30,000, VMT/Hh increases with income as expected, but levels off and falls slightly at higher incomes up to $100,000 per person, as shown in Fig. 7.

The best San Francisco model for VMT/Veh using variables available in all three regions is the same as in Table III, but with a function for Zonal Transit Density in place of that for Households/Total Acre. Tr gives an R^2 of 44.1%, which is slightly better than the 43.8% in the above table. But in the other two regions, Tr in place of H/RA reduced the R^2 to 40.0% for Chicago and 37.6% for LA, substantially poorer than the Hh/Tot Acre fit. So the recommended equations use Hh/Tot Acre.

In all three cities, the R^2 for VMT/Veh is much lower than the R^2 for Veh/Hh, indicating that neighborhood conditions more strongly impact the decisions on how many vehicles to have available than they do each decision to use the vehicles on hand. However, since Veh/Hh varies much more from zone to zone (1 s.d. equals $\pm 25\%$ for San Francisco) than does VMT/Hh ($\pm 9\%$), Veh/Hh is more important, and the R^2 for the resulting VMT/Hh is almost the same as for Veh/Hh.

Data for center proximity was only available for the San Francisco region, so none of the fits in Table III are based on it. The Veh/Hh fit in Table III is already highly significant, and center proximity added no significance. However, for vehicle use, center proximity added about 5% to the total variation explained, giving a total R^2 of 53.9% for the San Francisco region. This suggests that the impacts of CP, while not measured in Chicago and Los Angeles, should be further explored. The equations in Table II provide a high explanation of variation.

EXTENDING THESE FINDINGS TO OTHER METRO AREAS

The equations and their results are strikingly similar between the three regions. This suggests that a single equation might represent all three metro areas, or even other areas. To test this, we fit the data for each region as being proportional or linearly related to the predictions developed for the other regions; for instance, the ability of the Chicago equations to predict San Francisco zonal auto ownership. We found that for the Veh/Hh, a simple proportionality constant gave fits that were lower than the fits in Table III by only 3% to 14% in R^2. The losses are larger for the VMT/Veh fits, and the fit of the Chicago function to the San Francisco data is not significant. For the linear fits the loss in R^2 ranges from 2% to 6% for Veh/Hh, and from 1%–14% for VMT/Veh. All these later fits appear significant.

Combining the three regional data sets into one and fitting it gives similar results to what we found above. With no allowance for regional variations, the Veh/Hh fit reduces the R^2 shown in Table III by 3–13%, as shown in Table IV, analysis 1. Using separate scale parameters for each region, the R^2 increases to within 2% of the values found in Table III for all three regions as shown in Table IV, analysis 2. With no regional normalizations, the VMT/Veh fit is again not significant in Chicago, but is fairly good in the other two regions. Scaling the fits separately for each region reduces R^2 by 2% (LA), 3% (SF) and 9% (Chicago), as shown in Table IV, analysis 3. These fits are all still statistically significant, although they are not as good as individual fits to each region.

These results suggest that these models have identified important factors, but may have missed some that cause regional differences. Possible additional factors are:

- Age and attractiveness of the central city;
- Differences in attitude toward driving and public transit;
- Differences in the cost of living, or of owning and operating a vehicle;
- Cost or quality (pleasantness, reliability, connectivity and safety) of transit;

– Highway congestion and travel times;
– Government or private programs to encourage use of transit or carpooling; and
– Climate.

The average Veh/Hh and the independent variables for predicting zonal Veh/Hh (net residential density, per capita income, household size and transit) are available for each zone from the census, local or regional planning departments, and transit agencies. This data, however, is not useful for improving the fits to the regional data. The problem is that the scale factor gives the vehicle ownership at the average values of the independent parameters, and not the average ownership of the region. The ratio between these two values is not constant, so regional normalization is not useful. Fortunately, as we have already seen, the fit that was developed without regional normalizations fits fairly well.

While extensive odometer readings or other measures of VMT by zone are not available in many metropolitan areas outside California and Illinois, the independent variables for predicting VMT/Veh (gross residential density, household size, pedestrian/bicycle friendliness and per capita income) are generally available from the census and local or regional planning departments. As we showed above, one fixed set of parameters is not adequate for predicting VMT/Veh for different regions. Fortunately, estimates for the average VMT/Veh for whole metro areas, usually based on fuel consumption available from state Departments of Transportation, can be used to adjust the predicted zonal VMT/Veh.

We fit all three regions' data aggregated together, using the average VMT/Veh for each region as the scaling factor. Because the function is non-linear, the average of the function over the independent values is not equal to the value of the function when evaluated at the average values of the independent parameters. To make the equations return a value other than the average VMT/Veh at the average value of the independent parameters required adding a scaling factor (0.96165 in the equation below). This procedure turned out to be reasonably successful; giving R^2 of 37%, 39% and 40%, respectively for Chicago, Los Angeles and San Francisco, as shown in Table IV, analysis 4. These are only 3–10% of variance explained below the equations

TABLE IV Using the equations to predict Veh/Hh and VMT/Hh in other regions

1. **Veh/Hh fit**	SF style fit with no regional variation in the parameters. SF regional values used for normalizations			
Sum. Sq. Err.	Deg. Freedom	Mean. Sq. Er.	Rt. MSE	R^2
24140	2815	8.58	2.93	0.82
Parameter	Estimate	Approx. STr. Err	t	prob
Veh/Hh	1.946	0.00867	224.51	0
Ln (Veh/Hh)	0.666	0.004	149.523	0
Hh/RA-exp	−0.253	0.079	3.213	0.00132705
Hh/RA-const	21.204	9.726	2.180	0.029334168
$/Cap-const	0.0001185	0.0000036	32.837	1.7106E-200
$/Cap-exp	0.792	0.021	38.356	2.5647E-259
Pop/Hh	0.862	0.064	13.433	6.41535E-40
Tr-exp	−0.169	0.015	11.594	2.14025E-30
Tr-const	11.177	1.926	5.804	7.18199E-09
	TSS	ESS	R^2	
SF	30083	3871	0.87	
LA	60695	14639	0.76	
Chi	34279	5630	0.84	
Total	125057	24140		
2. **Veh/Hh fit.**	Regional average values of the independent parameters and best fit Veh/Hh			
Sum. Sq. Err.	Deg. Freedom	Mean. Sq. Er.	Rt. MSE	R^2
18572	2813	6.60	2.57	0.86
Parameter	Estimate	Approx. STr. Err	t	prob
Hh/RA-exp	−0.195	0.022	8.699	5.58303E-18
Hh/RA-const	5.210	1.252	4.161	3.26847E-05
$/Cap-const	0.000134	0.0000029	46.640	0
$/Cap-exp	0.882	0.019	46.682	0
Pop/Hh	0.716	0.044	16.109	6.43313E-56

Tr-const	18.202	4.067	4.475	7.94264E-06
Tr-exp	–0.142	0.017	8.446	4.7736E-17
The following three parameters replace Veh/Hh scale parameter (1.946 above)				
pSF	1.715	0.009	186.671	0
pLA	1.920	0.0073	261.332	0
pChi	1.669	0.010	165.851	0
	TSS	ESS	R^2	
SF	30083	3481	0.88	
LA	60695	13211	0.78	
Chi	34279	1880	0.95	
Total	125057	18572		
	F-statistic for added variables			421.64
	Probability that added variables are false			6.9385E-161
	(assumes linear model – which is an approximation)			
3. **VMT/Veh fit.**	Best fitting VMT for each region with regional average values in body of fit.			
Sum. Sq. Err.	Deg. Freedom	Mean. Sq. Er.	Rt. MSE	R^2
57773	2815	20.52	4.53	0.53
Parameter	Estimate	Approx. STr. Err	t	prob
SF-VMT	9828	26	383.0	0
Hh/TA-exp	–0.0551	0.0041	13.6	1.3E-03
Hh/TA-const	0.3921	0.1099	3.6	0.0293342
Ped	–0.0275	0.0022	12.7	1.7E-200
Pop/Hh	0.0232	0.0032	7.3	2.6E-259
$/Cap	–0.0573	0.0074	7.8	6.4E-40
LA-VMT	10334	35	295.2	2.14E-30
Chi-VMT	10884	51	213.3	7.18E-09
		General fit versus individual cities		
	SS	TSS	R^2	
SF	16713	28296	0.41	
LA	35250	58787	0.40	

(*continued on next page*)

Table IV (continued)

Chicago	5810	9343	0.38	
Total	57773	96426		
4. **VMT/Veh fit**.	Regional average VMT/Veh as parameter Regional averages in body of fit for normalizations			
Sum. Sq. Err.	Deg. Freedom	Mean. Sq. Er.	Rt. MSE	R^2
58511	2817	20.77	4.56	0.52
Parameter	Estimate	Approx. STr. Err	t	prob
Hh/TA-exp	−0.0529	0.0039	−13.4	1.0E-39
Hh/TA-const	0.3955	0.1134	3.5	0.000493
PBFS	−0.0279	0.0022	−12.8	1.7E-36
Pop/Hh	0.0224	0.0031	7.1	1.1E-12
$/Cap	−0.0565	0.0073	−7.7	1.4E-14
Regional Scale	0.9616	0.0014	664.6	0
	SS	TSS	R^2	
SF	16908	28296	0.40	
LA	35724	58787	0.39	
Chicago	5880	9343	0.37	
Total	58511	96426		

developed specifically for each metro area. This procedure would be easy to apply to other metropolitan areas, and has the advantage of not requiring zonal VMT/Veh measurements. The resulting equation is:

$$\frac{\text{VMT}}{\text{Veh}} = 0.96165\left(\frac{\text{RegAvgVMT}}{\text{Veh}}\right)\left(\frac{0.3955 + (\text{H/TA})}{0.3955 + (\text{AvgH/TA})}\right)^{-0.0529} \times \left(\frac{1 + 0.0224(\text{P/H})}{1 + 0.0224(\text{AvgP/H})}\right)\left(\frac{1 - 0.0279\sqrt{\text{Ped}}}{1 - 0.0279 Avg\sqrt{\text{Ped}}}\right) - 0.0565\left(\frac{\$}{\text{P}} - \frac{\text{Avg\$}}{\text{P}}\right)$$

where VMT/Veh is Vehicle Miles Traveled/Vehicle, avg is the average or mean over the region, H/TA is Households/Total Acre, \$/P is Income/Capita, P/H is Persons/Hh and $\sqrt{\text{Ped}}$ is the square root of Ped/Bicycle Friendliness.

This shows that the VMT/Veh equation developed for the three metro areas combined can be used with the average regional VMT/Veh in metro areas where zonal VMT/Veh measurements are not available. Since the VMT/Hh is dominated by the variability in VEH/Hh, the percentage of variation explained by the predicted VMT/Hh should be only 1 or 2% below that for an equation developed with zonal VMT/Veh measurements.

CONCLUSIONS AND DIRECTIONS FOR FURTHER STUDY

This analysis shows that urban design and transportation infrastructure have a highly significant influence on auto ownership and distance driven for neighborhoods in three large U.S. cities, even after the correction for household size and income effects. Using the models we derived, observed differences in density and transit can explain over 3 : 1 variations in vehicle miles driven per household for a constant level of income and household size.

The analysis further suggests that an even higher degree of variance, particularly in distance driven per car, may be explainable by expanding the set of explanatory variables and performing more statistical analysis. It may also be useful to analyze how the usage of other modes – transit, walking or bicycling – varies with urban design and socio-economic variables.

More broadly, the very strong statistical correlations observed in these three metro areas, and the extent to which the results are similar, along with the findings of Newman and Kenworthy [1] and others, suggest that neighborhood design may have a universal relationship to car ownership and driving. It is particularly interesting that similar relationships hold up for a flat terrain bordered on one side by a lake (Chicago), a hilly/mountainous area where most of the development is limited to the valleys and lower hills (LA) and a hilly/mountainous area surrounding a large bay where most of the development is limited to the valleys and lower hills (SF). These relationships may differ as we compare smaller metropolitan areas with bigger ones. And it is plausible from theory that the relationships may also be a function of gasoline price or automobile tax policies. We were unable to test for such price effects because the range of variation was too small, but an expanded database (e.g., comparisons between Europe and the U.S.), might help clarify such effects. Certainly the consistency of these results with earlier studies such as Newman and Kenworthy suggests that the search for global explanatory equations for driving behavior might be fruitful [15].

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[1] Peter Newman and Jeffrey Kenworthy (1989). *Cities and Automobile Dependence: An International Sourcebook*, Gower Publishing.

[2] Newman and Kenworthy's data suggest that the decrease in mileage with density is not linear, but is most closely approximated by density raised to a power. This can also be expressed as the percent decrease in vehicle miles traveled as density doubles. Such expression is easier for most people to comprehend than the more abstract concept of raising density to a power.

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[13] Had direct measurements of the continuity, width and quality of sidewalks, nearness of buildings to the sidewalk, and traffic safety been available, we would have preferred using them to using the mean year the housing was built.

[14] The calculated fit to the data is weighted by the standard errors of the mean values, which are just the standard deviations divided by the square root of the number of households, vehicles, etc.

[15] Clement Dinsmore of the Surface Transportation Policy Project (STPP); Scott Bernstein, Jacquelyne D. Grimshaw and James K. Hoeveler of the Center for Neighborhood Technology (CNT); and Donna Liu of the Natural Resources Defense Council (NRDC) participated in this study. The study was sponsored by the Location Efficient Mortgage^{SM} (LEM) Partnership, consisting of NRDC, CNT and STPP. The study was financed by the U.S. Department of Energy's Office of Transportation Technology, the U.S. Department of Transportation's Federal Transit Administration (FTA) and the U.S. Environmental Protection Agency's Urban and Economic Development Division, as well as by private foundations. Vehicle Miles Traveled (VMT) for California autos were supplied by the California Bureau of Automotive Repair, with the ZIP codes appended by the California Energy Commission. Illinois odometer readings and ZIP codes were supplied by the Illinois Environmental Protection Agency.

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