THE EFFECTS OF URBAN SPATIAL STRUCTURE ON TRAVEL DEMAND IN THE UNITED STATES

Antonio M. Bento, Maureen L. Cropper, Ahmed Mushfiq Mobarak, and Katja Vinha*

Abstract—We examine the effects of urban form and public transit supply on the commute mode choices and annual vehicle miles traveled (VMTs) of households living in 114 urban areas in 1990. The probability of driving to work is lower the higher are population centrality and rail miles supplied and the lower is road density. Population centrality, jobs-housing balance, city shape, and road density have a significant effect on annual household VMTs. Although individual elasticities are small absolute values (≤0.10), moving sample households from a city with the characteristics of Atlanta to a city with the characteristics of Boston reduces annual VMTs by 25%.

I. Introduction

SINCE the Second World War the predominant pattern of urban growth in the United States has been one of low-density development and employment decentralization, accompanied by a rapid increase in automobile ownership and vehicle miles traveled (VMTs) (Mills, 1992; Mieszkowski & Mills, 1993; Glaeser & Kahn, 2001). The last 15 years, however, have witnessed a reaction to urban sprawl in the form of "smart growth" initiatives. Attempts to limit urban growth or to change its form are motivated by three concerns—to preserve open space and foster urban development that is more aesthetically appealing, to reduce the cost of providing public services, and to reduce dependence on the automobile and the externalities associated with automobile use that have accompanied urban sprawl.[1]

This naturally raises the question: how does urban form—whether measured by the spatial distribution of population or employment or the public transit network—affect vehicle ownership and the number of miles driven by households in the United States? This paper addresses this question by combining measures of urban form and transit supply in 114 urban areas in the U.S. with data from the 1990 Nationwide Personal Transportation Survey. We ask whether measures of urban sprawl—measures that describe city shape, spatial distribution of population, and jobs-housing balance—and the supply of public transit affect the VMT and commute mode choices of U.S. households.

Previous attempts to answer these questions have relied either on city-level observations or on studies of household data in which measures of urban form are endogenous. City-level studies that correlate measures of automobile use with population density or density gradients (Levinson & Kumar, 1997; Newman & Kenworthy, 1989; Malpezzi, 1999) often fail to control for other variables that affect automobile ownership and mode choice. Analyses of vehicle ownership and VMT using household data often include measures of urban form, but ones that are clearly subject to household choice. For example, the population density of the census tract or ZIP code in which the household lives is often used as a measure of urban sprawl (Train, 1986; Levinson & Kumar, 1997; Boarnet & Crane, 2001), and the distance of a household's residence from public transit or from the central business district (CBD) as a measure of availability of public transportation (Train, 1980; Boarnet & Sarmiento, 1998; Crane & Crepeau, 1998; Boarnet & Crane, 2001).[2] Coefficient estimates obtained in these studies are likely to be biased if people who dislike driving locate in areas where public transit is more likely to be provided.

We address these issues by adding city-wide measures of sprawl and transit availability to the 1990 Nationwide Personal Transportation Survey (NPTS). The survey contains information on automobile ownership and annual miles driven for over 20,000 U.S. households and on the commuting behavior of workers within these households. For NPTS households living in the urbanized portion of 114 metropolitan statistical areas (MSAs)[3] we construct measures of urban form—measures of city shape (how close to circular the city is), the density of the road network, the spatial distribution of population (how close to the CBD the population is located), and the jobs-housing balance. To characterize the transport network we compute city-wide measures of transit supply—specifically, bus route miles supplied and rail route miles supplied, normalized by city area.

We use these data to estimate two sets of models. The first is a model of commute mode choice (McFadden, 1974), in which we distinguish four alternatives—driving, walking/bicycling, commuting by bus, and commuting by rail. We estimate this model using workers from the NPTS who live in one of the 26 cities in the U.S. that have some form of rail transit, as well as data on our other measures of urban form. We also estimate a logit model to explain whether or not a

Received for publication May 6, 2003. Revision accepted for publication December 29, 2004.

* University of Maryland; University of Maryland and The World Bank; University of Colorado, Boulder; and Universidad de Los Andes, Colombia, respectively.

The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the World Bank, its Executive Directors, or the countries they represent. We would like to thank Richard Arnott, Matthew Kahn, Jordan Rappaport, Julio Rotemberg, Zmarak Shalizi, Ken Small, Margaret Walls, two anonymous referees, and participants at seminars at Columbia University, Stanford University, University of California at Berkeley, the NBER Summer Institute July 2001, ASSA Meetings January 2002, World Congress of Environmental and Resource Economists 2002, and Colorado Environmental and Resource Economics Workshop 2002.

[1] For a discussion of the effects of these externalities on urban spatial structure see Brueckner (2001) and Bento and Franco (forthcoming). Kahn (2000) discusses the environmental impact of suburbanization.

[2] For a review of the literature, see Badoe and Miller (2000).

[3] We use the 1990 boundaries of urbanized areas associated with the 114 metropolitan areas in our study. These boundaries are defined by the U.S. Census Bureau. Urbanized areas are those that have a population density that is greater than 1,000 per square mile and a total population of at least 50,000.

The Review of Economics and Statistics, August 2005, 87(3): 466–478

worker drives to work, using data from the 114 cities for which we have both sprawl and transit data. The second set of models explains the number of vehicles owned and miles driven per vehicle for households living in these same 114 urban areas.

The rest of the paper is organized as follows. Section II reviews the relationship between urban form and travel demand in the urban economics literature, describes our empirical measures of urban form, and compares these measures with traditional sprawl measures. It also describes our city-wide transit variables. Section III presents the results of our commute mode choice models, and section IV our models of automobile ownership and VMTs. Section V examines the implication of moving our sample households to cities with different vectors of transit and sprawl characteristics, and section VI concludes.

II. The Relationship Between Urban Form and Travel Demand

A. Theory

Urban economics predicts that the number of miles a household travels and the mode it chooses for different trips will depend on the structure of the city in which the household resides—on the distribution of population and employment within the city, on the size of the city (in square miles), and on its road and transit networks.

In the simple monocentric model (Muth, 1969) in which all employment is located in the CBD and the number of trips per worker is fixed, the number of miles a household travels is proportional to how far from the CBD it locates (τ). This depends on the rent gradient it faces and on the marginal cost of travel, which, in general, varies with distance from the CBD. To allow for congestion, Wheaton (1998) suggests that the marginal time cost of travel at a point varies directly with population density and inversely with the proportion of land devoted to roads at that point. The household's travel demand, which equals the number of one-way trips to the CBD times τ, thus depends (through choice of τ) on the road network and on the distribution of population throughout the city.

Modifications to the monocentric model (Michelle White, 1977, 1986, 1988) have allowed firms to move out of the CBD, implying that employment is located throughout the metropolitan area. The spatial distribution of firms (and associated wage gradient) affects commute lengths by affecting where households choose to live and where they choose to work. By determining the location of services and retail establishments, the spatial distribution of firms also affects the length of nonwork trips.[4]

The monocentric model can also be modified to allow for public transportation. Assume that the household can travel either by public transit or private auto (Bento et al., 2003). There is a marginal time cost and a marginal price for public transit at each point in the city, just as there is a marginal dollar cost of driving and a marginal time cost that depends, following Wheaton, on the density of the road network and of population at each point in the city. It is an easy matter to construct a model in which the household determines the number of trips to make by private auto and the number of trips to make by public transit. The frequency of transit service and the numbers of transit stops and route miles supplied, by influencing the marginal time cost of public transit, will affect commute mode choice and the number of miles driven annually.

B. Measures of Urban Form

The previous subsection suggests that VMT and commute mode choice depend on three aspects of urban form—the road network, the pattern of residential land use, and the distribution of employment (also a proxy for the distribution of services)—throughout the urban area. The question is: How should these dimensions of urban form be measured empirically? Our choice among alternative measures of each dimension of urban form is guided by two principles: the set of measures should capture different aspects of urban form (that is, they should not be too highly correlated with each other), and, to facilitate interpreting our results, it should be possible, conceptually, to vary one measure while holding the others constant.

Road Network: A complete description of the road network in a circular city would include describing road density in successive annuli around the CBD, as well as the pattern of roads (for example, a radial network with or without ring roads). The situation is more complicated in a city that is not radially symmetric. We use two measures to describe the road network. The first is a measure of *city shape*. The second is a measure of *average road density* for the urban area.

City shape. Theory suggests that trip distances should be longer in long, narrow cities than in circular cities with radial road networks. To measure how much an urbanized area deviates from a circular city, we have circumscribed each city with an ellipse equal in area to the urbanized area of the city, and have measured the major and minor axes of the ellipse. The ratio of the minor to the major axis, our measure of city shape, ranges between 0 and 1, with 1 indicating a circular city.[5]

Road density. For each urban area, miles of road are multiplied by average road width (for different categories of

[4] This literature has also pointed out how differences in income and in tastes (due to differences in family composition) may influence commute lengths. Assuming that the income elasticity of the demand for housing exceeds the income elasticity of commuting costs, higher income persons should locate farther from the CBD and have longer commutes. White (1977) shows under plausible conditions that female workers in two-earner households should have shorter commutes than either single or married male workers.

[5] See the Data Appendix in Bento et al. (2003) for a more complete description of the measures.

TABLE 1.—EXAMPLES OF THE POPULATION CENTRALITY MEASURE

City	Distance from CBD	% of Total Distance	Actual Population	Distance-Weighted Population	Cumulative Actual Population	Cumulative Distance-Weighted Population	Measure of Population Centrality
A	2	20	5	10	50	21	
	6	60	3	18	80	58	0.1694
	10	100	2	20	100	100	
B	1	20	2	2	20	6	
	3	60	3	9	50	31	0.1130
	5	100	5	25	100	100	

road) and divided by the size of the urbanized area (in square kilometers).

Pattern of Residential Land Use: In a circular city the natural measure of the pattern of residential land use is the population density gradient (McDonald, 1989). The density gradient describes the centralization of population around the CBD. The density gradient, together with the city radius (or city area) and the intercept of the density function, completely describes the distribution of population within a monocentric city. An alternative to the density gradient as a measure of centrality is the percentage of population living at various distances (within 5 km, within 10 km, and so on) from the CBD (Glaeser & Kahn, 2001). Both measures of course require that one identify a single CBD. The population density gradient is the more restrictive of the two measures, as the conventional negative-exponential gradient assumes that density declines monotonically with increasing distance from the CBD. Because of the poor fit of exponential density gradients in many cities (Malpezzi, 1999), we reject the population density gradient as a measure of population distribution. We also reject as a measure of decentralization the percentage of population living within 5, 10, 15, and 20 km of the CBD. The correlation among these measures and between each measure and city area violated our criterion that different measures of urban form not be too highly correlated.[6]

Population centrality. To create a measure of population centrality that is less correlated with city area, we compare in percentage terms the cumulative distribution of population at different distances from the CBD (as a percentage of maximum distance from the edge of the city) with the cumulative distribution of population at these distances in a sprawled city. Table 1 compares two cities with equal populations: City A, with a radius of 10 miles, and City B, with a radius of 5 miles. The population in City A is, however, more *centralized*: Half of the population lives within 20% of the distance from the CBD to the edge of the city, and 80% of the population lives within 60% of that distance. The corresponding figures for City B are 20% of the population within 20% of the distance, and 50% of the population within 60% of the distance.

With what should the cumulative distribution of actual population be compared to measure centrality? A possible definition of a sprawled city is one with a uniform population density, implying that x% of the total population lives between the CBD and x% of the distance to the city center. Unfortunately, this definition is quite sensitive to the definition of the city boundary: adding a small number of people far from the CBD will lower the average population density and make the city appear much less sprawled.

We instead use a definition of a sprawled city in which the actual population at each distance from the CBD is weighted by distance. Our definition of sprawl weights a person living on the city edge 10 times as much as a person living 1 mile from the CBD. This may be justified by the fact that the person living 10 miles from the CBD must travel 10 times as far to reach the city center as a person living 1 mile from the CBD. Our population centrality measure is computed by averaging the difference between the cumulative population in annulus n (expressed as a percentage of total population) and the cumulative distance-weighted population in annulus n (expressed as a percentage of total distance-weighted population). Formally, our centrality measure is given by

$$\frac{1}{N}\sum_{n=1}^{N}\left(\frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{N} P_i}-\frac{\sum_{i=1}^{n} P_i d_i}{\sum_{i=1}^{N} P_i d_i}\right), \tag{1}$$

where i, $i = 1, \ldots, N$, indexes annuli around the CBD, d_i is the distance of annulus i from the CBD, and P_i is the population of annulus i.[7] In our example, the centrality measure equals 0.1694 for City A and 0.1130 for City B, with larger numbers indicating more centralized cities.[8,9]

[6] The correlation coefficients between land area and percentage of the population living within various distances from the CBD are as follows: 5 km (−0.61), 10 km (−0.66), 15 km (−0.73), 20 km (−0.73). We also computed similar measures for cities with multiple CBDs, where distances were measured from a point equidistant from the CBDs. These measures, too, were highly correlated with city area.

[7] If we were to define a sprawled city as one with uniform population density, the term on the right in the parentheses would be $-d_n/d_N$.

[8] In the example calculation, we treat all persons living within 2 miles of the CBD as living at a distance of 2 miles, all persons living 2–5 miles from the CBD as living at a distance of 5 miles, and all persons living 5–10 miles from the CBD as living at a distance of 10 miles.

[9] It is easy to verify that the centrality measure for City A is 0.166 when a sprawled city is defined as one with uniform population density. Adding a million people 20 miles from the CBD of City A, however, has a much larger impact on the latter measure (it increases it by 81%) than on our measure (which it increases by 21%).

Because our population centrality measure does not capture city size, we supplement this with the size of the urban area in square miles.

Distribution of Employment: The set of possible employment locations in an urban area clearly affects commute lengths. Similarly, the distribution of employment in commercial and retail occupations, relative to the distribution of residences, is likely to affect the distance traveled for nonwork trips. There are several ways in which the distribution of employment could be measured. One is a measure of employment centrality similar to our measures of population centrality; another is the employment density gradient. We believe, however, that for studying the determinants of driving behavior, it is more important to measure the location of employment relative to population in a way that is independent of the number or location of CBDs. To measure the spatial balance of jobs versus housing we have borrowed a measure from the residential segregation literature (Massey & Denton, 1988), which we compute using employment data from *1990 Zip Code Business Patterns* (U.S. Census Bureau).[10]

Balance of jobs versus housing. To measure how evenly jobs are distributed relative to population, we order ZIP codes in each city from the one having the smallest number of jobs to the one having the largest and plot the cumulative percentage of jobs (y-axis) against the cumulative percentage of population (x-axis) to obtain a Lorenz curve. The 45-degree line represents an even distribution of jobs versus population. Our *balance* measure (Massey and Denton's Gini coefficient) is the area between the Lorenz curve and the 45-degree line, expressed as a proportion of the area under the 45-degree line. Larger values of this measure imply a less even distribution of jobs versus housing.

How different are our measures from traditional measures of urban sprawl? Urban sprawl is most often measured using average population density in a metropolitan area. This is clearly a blunt measure of sprawl, and is only weakly correlated with population centrality ($r = 0.16$), jobs-housing balance ($r = 0.06$), or city shape ($r = -0.10$). That population centrality and jobs-housing balance capture different aspects of sprawl than average population density is illustrated by comparing the ranking of urban areas by these three measures.[11] Using a rank of 1 to indicate the least-sprawled urbanized area in our sample, the New York urban area (which includes northern New Jersey and Long Island) is, not surprisingly, the 3rd least sprawled urbanized area in terms of population density. It is also the 5th least sprawled city in terms of population centrality; however, it is the 95th least sprawled city in terms of jobs-housing balance, and the 92nd least sprawled in terms of road density. San Diego, which is the 13th most densely populated city in our sample, is the most sprawled city in terms of job-housing balance. Miami, the 2nd most densely populated city in the sample, is the least circular city. These comparisons illustrate the fact that our measures capture dimensions of urban structure that are missing in the population density measure.

C. *Measures of Transit Supply*

Reliance on public transportation, whether for commute or for noncommute trips, depends on the extent of the transit network. We measure the extent of the public transit network by the number of bus route miles supplied in 1993 divided by the size of the urban area (in square kilometers), and by the number of rail route miles supplied in 1993 divided by the size of the urban area.[12]

Not surprisingly, our measures of transit supply are correlated with each other, as well as with measures of urban form.[13] Cities that are larger in area and more densely populated tend to have a greater supply of both rail and bus transit. The supply of nonrail transit is twice as great in the 26 rail cities in our sample as in the other 88 cities. This may indicate an attempt to link rail and bus networks or that similar factors (such as, population density) favor both.[14] Higher road density is also correlated ($r = 0.39$) with greater supply of bus transit; however, population centrality, jobs-housing balance, and city shape are not highly correlated with public transit supply or with road density.

III. Commute Mode Choice Models

In this section we link the measures of urban form and transit supply described in the previous section to the 1990 Nationwide Personal Transportation Survey (U.S. Department of Transportation, 1990) to explain the "usual mode" of commute to work of workers living in the 114 cities for which we have data on urban form and transit supply.[15] Specifically, for the 26 cities with rail transit, we estimate multinomial logit models of mode choice in which workers choose among (a) driving to work, (b) taking rail transit, (c) taking nonrail transit, and (d) walking or bicycling. For all 114 cities we estimate a logit model to explain whether or not a worker drives to work.

A. *Models of Commute Mode Choice*

Our empirical model of commute mode choice is a random utility model in which the observable component of

[10] We also computed the average weighted distance of jobs from housing in each urban area—Galster et al.'s (2000) proximity measure, originally proposed by Michael White (1986); however, it was very highly correlated with city area ($r = 0.80$).

[11] Appendix B of Bento et al. (2003) presents summary statistics for sprawl and transit variables for all cities in our sample.

[12] Rail (bus) route miles represent the number of miles traveled by all railroad cars (buses) during a year.

[13] Table 2 of Bento et al. (2003) presents pairwise correlations between measures of sprawl and transit supply.

[14] The correlation of population density with rail supply is 0.48; with bus supply, it is 0.73.

[15] We use the 1990 NPTS because it is the closest NPTS to the years used to compute measures of sprawl and transit supply.

indirect utility from commute mode w for household i (V_{iw}) depends on income, on travel costs, on measures of urban form and transit availability, and on worker and household characteristics that influence utility. We include in V_{iw} the age, race, education, and gender of the worker, the numbers of adults and children in the household, and the household income. The cost per mile of driving is calculated as the city-specific gasoline price divided by the average fuel efficiency of cars owned by households in the same income class as the commuter.[16] Data on the price of rail or bus trips were available for too few cities to make these variables usable.

Also included in V_{iw} are measures of urban form and transit supply. We treat these measures as exogenous to the individual worker, an assumption that is more difficult to justify for road density and rail and bus supply than for measures of urban form such as city shape. The problem is that city attributes that we do not measure (for example, crime near public transit) may affect both people's propensity to ride transit and the supply of route miles. Ideally, measures of transport supply should be modeled together with individual mode choice. The same measures of urban form and transit supply are included in both the mode choice and driving models, with a dummy variable added to the latter to capture whether a city has rail service at all.

B. *The NPTS Worker Sample*

The 1990 NPTS consists of 22,317 households living in urban and rural areas of the U.S. Of these households, 9,719 lived in the 114 urban areas for which we have data on both sprawl and transport measures. These households constitute our core sample. To estimate the multinomial logit model of commute mode choice, we focus on the 26 cities with some rail transit. The 6,470 workers in our sample households in these cities are used to estimate the commute mode choice model. We distinguish four usual commute modes—private transportation, nonrail transit, rail transit, and nonmotorized transit. The percentage of workers using private transportation in our sample (79.7%) is lower than the average for all workers in the NPTS (85.4%). This is because workers in the New York urban area constitute approximately 30% of our sample of workers in rail cities. Approximately 6% of our rail city sample commute by bus (5% without New York) and 8% by rail (2% without New York); approximately 6% either bike or walk to work (with or without New York). In modeling the drive–no-drive decision, we use 11,426 workers in all 114 metropolitan areas, 85.4% of whom drive to work.

C. *Commute Mode Choice Results*

Results for our multinomial logit models appear in table 2. In both models the omitted mode is driving to work; hence all coefficients should be interpreted relative to this category. The table displays the coefficient of each explanatory variable for each mode, the ratio of the coefficient to its standard error, and (for significant variables) the marginal effect on the probability of selecting each mode with respect to the variable.[17] Because workers in the New York urban area constitute such a large fraction of our sample, we present results with and without New York.

The effects of household characteristics on commute mode choice accord with the literature. Income, race and education all have statistically significant effects on the probability that a commuter takes transit or walks to work. In both samples higher income workers are less likely to walk to work or take public transit than they are to drive. The income elasticity of bus, rail, and nonmotorized modes are well below 1 in absolute value in the full sample (-0.50, -0.25, -0.46, respectively), a result similar to McFadden (1974). The elasticities are somewhat higher when New York is removed from the sample: -0.74, -0.83, and -0.49 for bus, rail, and walking, respectively. Whites are significantly less likely to ride the bus or train than are other groups. A 10% increase in years of schooling raises the probability of riding rail by 1.1 percentage points in both samples; however, this implies quite different elasticities in each sample due to the baseline differences in the percentage of commuters taking rail to work. Results for gender and household composition are not robust, which accords with much of the literature on mode choice.[18]

In examining the effects of urban form and transit supply, two results stand out. The first is that the most robust effect of urban form, as measured by population centrality and jobs-housing balance, is to increase the probability of walking or bicycling to work. Population centrality increases the chances that a worker walks to work, with elasticities of 1.7 with and 2.3 without New York. In cities with greater jobs-housing balance, workers are more likely to walk to work; however, the magnitude of this effect is lower than for population centrality ($|\text{elasticity}| < 0.5$ in both samples).

The second result is that increasing rail (bus) supply increases the modal share for rail (bus) in both samples. The elasticity of the rail mode with respect to rail supply is, however, large (over 6) when New York is included in the sample, and is no doubt an artifact of the high modal share for rail in the New York area. When New Yorkers are excluded from the sample, the elasticity of the share of

[16] Details are given in Appendix C of Bento et al. (2003).

[17] Marginal effects are computed by increasing the value of an explanatory variable for each worker in the sample and predicting the probability that the worker selects each mode. The average of these predicted probabilities is compared with the average of the predicted probabilities before changing the explanatory variable. For integer and dummy variables a 1-unit change is evaluated; for continuous variables, a 10% change.

[18] Sarmiento (2000) in a review of the effects of gender and household composition on travel, notes that the effect of gender on mode choice varies considerably from one study to another.

TABLE 2.—MODE CHOICE MODELS

	Whole Sample						Excluding New York City					
	Bus		Rail		Nonmotor		Bus		Rail		Nonmotor	
Variable	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡
Age of worker	−0.061	−3.65	−0.056	−2.78	−0.080	−4.92	−0.071	−4.44	−0.039	−2.50	−0.091	−5.57
	(3.97)***		(4.89)***		(4.84)***		(2.84)***		(0.89)		(3.49)***	
Age squared	0.001		0.000		0.001		0.001		0.000		0.001	
	(4.33)***		(3.72)***		(4.70)***		(3.07)***		(0.66)		(3.21)***	
Indicator for female worker	0.577	+58.5	0.303	+17.2	0.148	+7.1	0.270		0.118		0.066	
	(2.33)**		(2.47)**		(1.18)		(1.20)		(0.41)		(0.45)	
Number of adults in the household	0.004		0.041		−0.018		−0.017	−2.23	0.249	+25.5	−0.014	−1.79
	(0.06)		(0.85)		(0.55)		(0.13)		(3.03)***		(0.23)	
No. of children aged 5–21	0.035	+3.17	−0.046	−3.80	0.026	+3.08	−0.121	−9.50	−0.080	−8.33	−0.073	−4.92
	(0.41)		(2.48)**		(0.45)		(2.04)**		(0.85)		(1.14)	
Indicator for female workers with children	−0.936	−46.1	−1.562	−67.5	−0.387	−14.9	−0.129		−0.490		0.328	
	(1.94)*		(7.30)***		(0.89)		(0.39)		(0.89)		(1.63)	
Log of income	−0.640	−0.50	−0.460	−0.25	−0.521	−0.46	−0.848	−0.74	−0.917	−0.83	−0.665	−0.49
	(4.13)***		(4.08)***		(4.23)***		(6.75)***		(4.47)***		(5.78)***	
Years of education	−0.018	−0.48	0.116	+1.27	0.012	+0.02	−0.021	−0.56	0.304	+4.58	0.024	+0.16
	(0.62)		(2.47)**		(0.65)		(0.46)		(6.08)***		(0.91)	
White household	−0.812	−46.1	−0.935	−45.8	−0.046	+11.7	−0.925	−58.2	0.185	+25.0	0.301	+42.6
	(6.49)***		(4.13)***		(0.17)		(5.47)***		(0.48)		(1.02)	
Black household	0.609	+70.4	0.092	−0.09	0.082	+1.54	0.459	+40.8	0.909	+109	0.324	+26.7
	(3.18)***		(0.70)		(0.38)		(1.58)		(2.89)***		(1.29)	
Annual rainfall	0.002		−0.047		−0.003		0.011		0.032		0.005	
	(0.10)		(2.16)**		(0.52)		(0.71)		(1.53)		(0.92)	
Annual snowfall	−0.215		0.169		−0.055		−0.200		−0.070		−0.061	
	(1.68)*		(1.01)		(1.22)		(1.61)		(0.34)		(1.72)*	
Gasoline cost of driving per mile	0.474		0.071		0.288		0.126		−0.800		0.021	
	(1.13)		(0.19)		(1.40)		(0.32)		(1.75)*		(0.15)	
Road density	0.406	+5.08	−0.773	−5.19	0.183	+2.0	0.529	+5.0	−0.042	−1.25	0.305	+2.6
	(1.80)*		(1.98)**		(1.90)*		(1.84)*		(0.14)		(3.46)***	
Supply of rail transit	6.990	−1.03	163.218	+6.58	16.048	−0.46	23.742	−0.56	193.274	+2.92	27.354	+0.16
	(0.29)		(4.75)***		(1.96)**		(0.95)		(5.60)***		(3.67)***	
Supply of bus transit	40.946	+0.63	36.893	+0.63	11.543	+0.07	19.484	+0.37	−35.599	−0.83	−7.092	−0.16
	(2.00)**		(0.93)		(1.40)		(0.64)		(1.34)		(1.09)	
Population centrality	18.837	+4.13	−46.633	−5.35	8.496	+1.69	28.466	+4.26	27.036	+3.75	17.161	+2.30
	(2.02)**		(2.59)***		(1.79)*		(2.07)**		(1.37)		(3.08)***	
Jobs-housing balance	−3.404	−0.95	−3.396	−0.76	−1.823	−0.46	−2.715	−0.93	1.059	+0.42	−1.315	−0.33
	(1.80)*		(0.85)		(3.07)***		(1.45)		(0.41)		(3.00)***	
City shape	0.735		0.465		0.129		0.539		−0.883		0.026	
	(1.23)		(0.43)		(0.55)		(0.89)		(1.14)		(0.12)	
Population density	−2.134	−2.70	0.300	+0.89	−0.659	−0.77	−2.238	−2.41	−0.646	−0.83	−0.779	−0.66
	(2.21)**		(0.21)		(1.58)		(2.28)**		(0.52)		(2.08)**	
Land area	0.112		−0.142		−0.031		0.125		0.234		−0.006	
	(0.74)		(0.63)		(0.54)		(0.89)		(0.88)		(0.12)	
Constant	−0.840		15.913		1.095		0.885		−0.045		1.201	
	(0.13)		(2.85)***		(0.35)		(0.17)		(0.01)		(0.56)	
Observations			6476						4468			

Driving to work is the omitted category.
* Significant at 10%; ** significant at 5%; *** significant at 1%.
† The column reports the coefficient for the variable and, in parentheses, the z-statistic. Standard errors are corrected for heteroskedasticity and clustered at each city.
‡ The column reports elasticity for continuous variables, and the percentage change in probability of choosing the mode in response to a unit change in discrete variables.

commuters taking rail with respect to rail supply falls to 2.9. The elasticity of bus ridership with respect to bus route miles is 0.63 in the full sample and 0.37 without New York.

Although transit supply and population centrality have nonnegligible percentage effects on rail, bus, and nonmotorized modal shares, their effect on miles driven to work is small, because only a small percentage of commuters take transit or walk to work. The coefficients in table 2 may be used to calculate the marginal effects of our measures of urban form and transit supply on the probability of driving to work. Rail supply has the largest effect on driving of all our sprawl and transit variables. A 10% increase in rail supply reduces the probability of driving by 4.2 percentage points, which translates into a 5.3% decrease at the mean, or an elasticity of 0.53. The effects of 10% increases in bus transit supply and jobs-housing balance are more modest, resulting in a decrease in the probability of driving of 1.3% and an increase of 1.9%, respectively.

To summarize the quantitative effects of sprawl and transit variables on the probability of driving to work using data from all cities in our sample, table 3 presents logit models of the drive–no-drive decision that are estimated using workers in all 114 metropolitan areas. These models are used to calculate the marginal effect of a 10% change in

TABLE 3.—BINARY LOGIT MODELS OF WORKERS' DRIVING DECISIONS

	Whole Sample		Excluding New York	
	Drive	ε†	Drive	ε†
Age of worker	0.056 (5.95)***		0.057 (4.16)***	
Age squared	−0.001 (5.81)***		−0.001 (4.52)***	
Indicator for female worker	−0.315 (3.12)***	−3.99	−0.193 (2.15)**	−1.86
Number of adults in the household	−0.011 (0.48)		−0.025 (0.65)	
No. of children aged 5–21	−0.050 (1.89)*		0.001 (0.04)	
Indicator for female workers with children	0.781 (1.76)*		0.016 (0.09)	
Log of income	0.554 (6.02)***	+0.07	0.696 (11.10)***	+0.06
Years of eduation	−0.023 (1.39)	−0.04	−0.021 (0.81)	−0.03
White household	0.558 (2.93)***	+8.22	0.209 (1.54)	+2.15
Black household	−0.359 (2.75)***	−4.89	−0.547 (3.66)***	−5.50
Annual rainfall	0.009 (2.07)**	+0.06	0.009 (2.20)**	+0.03
Annual snowfall	−0.060 (3.13)***	−0.01	−0.069 (3.58)***	−0.01
Gasoline cost of driving per mile	−0.117 (0.74)	−0.07	0.112 (0.61)	+0.06
Road density	0.061 (2.20)**	+0.08	0.055 (2.08)**	+0.04
Presence of rail transit	−0.291 (1.94)*	−3.64	−0.232 (1.72)*	−2.23
Supply of rail transit	−38.137 (5.30)***	−0.11	−51.250 (4.92)***	−0.03
Supply of bus transit	−26.762 (2.54)**	−0.07	−21.022 (1.83)*	−0.03
Population centrality	−4.407 (1.50)	−0.09	−6.137 (2.17)**	−0.10
Jobs-housing balance	0.894 (1.28)	+0.05	0.593 (0.88)	+0.02
City shape	−0.113 (0.37)	+0.00	−0.133 (0.43)	+0.00
Population density	0.178 (0.63)	+0.04	0.067 (0.25)	+0.01
Land area	0.039 (0.70)	+0.02	0.053 (1.07)	+0.01
Constant	−4.051 (2.14)**		−5.827 (3.34)***	
Observations	11,541		9533	

z statistics in parentheses. Standard errors are corrected for heteroskedasticity and clustered at each city.
* Significant at 10%; ** significant at 5%; *** significant at 1%.
† The column reports elasticity for continuous variables, and the percentage change in probability of choosing the mode in response to a unit change in discrete variables.

each variable on the probability that a randomly chosen worker drives to work, which is expressed as an elasticity.

Of all measures of urban form, population centrality and road density have the largest impact on whether a worker drives to work. Their effects, though comparable in magnitude to the effects of income and education, are small in absolute terms. A 10% increase in population centrality lowers the probability of driving by approximately 1 percentage point (elasticity = −0.09). If the average worker drives 6000 miles to work each year, this translates into a reduction of 54 miles annually.

The effects of rail and bus route miles on the decision to drive to work, though statistically significant, are generally smaller in magnitude than either population centrality or road density. The elasticity of driving with respect rail supply is −0.11 in the full sample but only −0.03 in the sample without New York. The corresponding elasticities for bus route miles are −0.07 with New York and −0.03 without New York. The magnitudes of these results are quite plausible in light of findings in the commute mode choice literature. Changes in bus or rail route miles supplied should affect mode choice through their impact on waiting times for bus and rail. McFadden (1974) reports elasticities of the probability of driving to work with respect to transfer wait times of 0.07 for bus and 0.11 for rail, which are in line with our findings.

The effects on driving we compute using the sample of workers in all 114 cities are usually smaller than—but in the same direction as—the corresponding effects from the mode choice models, which used workers in the 26 cities with some rail transit. For example, a 10% increase in the supply of rail transit reduces driving by 4.2 percentage points in the 26 city sample, and by only about 1 percentage point in the 114-city sample. A 10% decrease in jobs-housing balance increases the probability of driving by 1.5 percentage points in the smaller sample, but by only 0.4 percentage points in the larger sample.

IV. Models of Automobile Ownership and Annual VMTs

Urban form and transit supply may influence household VMTs by affecting either the number of cars owned or the number of miles each car is driven. We therefore estimate a model to explain the number of cars owned and the demand for VMTs per vehicle (Train, 1986; Goldberg, 1998; Walls, Harrington & Krupnick, 2000; West, 2004).[19] The model is estimated in two parts. The first part is a multinomial logit model that explains whether the household owns zero, one, two, or three or more vehicles. We then study the determinants of annual VMTs per vehicle separately for households that own one, two, or three or more vehicles. Because unobservable factors that explain the number of vehicles owned may be correlated with the error terms in the VMT-per-vehicle equations, we use the selectivity correction approach developed by Dubin and McFadden (1984) to estimate the demand for VMT equations.

A. *Specification of the Econometric Model*

We estimate a multinomial logit model of the number of vehicles owned and an equation for the average number of

[19] Train (1986) and Goldberg (1998) have also examined the determinants of vehicle ownership, but their focus differs from ours. Train uses models of vehicle ownership and utilization to forecast future VMTs. Goldberg models vehicle ownership and use to study the effects of corporate average fuel economy standards. Neither study examines the effects of urban form on travel demand.

miles driven, conditional on owning a vehicles. Let the indirect utility household i receives from owning a vehicles be written as the sum of an unobservable component u_{ia} and an observable component V_{ia} that includes household characteristics $\mathbf{Z}_i$ (which may affect utility); the price per mile of driving, φ; income net of the fixed costs of car ownership, $y_i - F_a$; and characteristics of the urban area in which the household lives, $\boldsymbol{S}_i$. The probability that the household owns a vehicles is given by

$$P_a = P(V_{ia} + u_{ia} > V_{ib} + u_{ib}), \quad \text{all } b \neq a, \qquad (2)$$
$$\text{where} \quad V_{ia} = \mathbf{B}_a\mathbf{Z}_i + \mathbf{\Gamma}_a\mathbf{S}_i + \beta_a\varphi_i + \gamma_a(y_i - F_a).$$

Conditional on a, the number of miles that a household drives, per vehicle, will depend on the same variables as enter the indirect utility function V_{ia},

$$(M/a)_i = \mathbf{D}_a\mathbf{Z}_i + \mathbf{\Omega}_a\mathbf{S}_i + \alpha_a\varphi_i + \delta_a(y_i - F_a) + \varepsilon_{ia}. \qquad (3)$$

Because the same unobservable variables that affect vehicle ownership are likely to affect miles driven, it is reasonable to assume that the error term in the average-miles-per-vehicle equation, ϵ_i, will be correlated with u_{ia}. We handle this by adding the selectivity correction factor derived by Dubin and McFadden to equation (3).

To estimate equations (2) and (3) we must measure the cost per mile driven and the fixed costs of vehicle ownership for each household. The fixed costs of vehicle ownership include the costs of interest and depreciation on the vehicle, as well as the cost of automobile insurance. The make, model, and vintage of each vehicle the household owns are recorded in the NPTS. However, to avoid endogeneity problems (for example, the chosen make and model may reflect the household's preferences for driving), we estimate the cost per mile and fixed costs of vehicle ownership for a typical household in household i's income class. [Appendix C of Bento et al. (2003) describes our calculation of the fixed costs of vehicle ownership and the price per mile traveled.] The price per mile is the price of gasoline in the household's MSA divided by the average fuel efficiency (miles per gallon) of vehicles owned by households in the household's income group. Household characteristics ($\mathbf{Z}$) include the number of persons in the household classified by age and work status, the race of the household head, and the number of years of schooling completed by the most educated person in the household. $\boldsymbol{S}$ includes our measures of urban form and transit supply, as well as annual rainfall and annual snowfall.

These models are estimated using all households in the 1990 NPTS living in the 114 urban areas for which city-wide sprawl and transit measures have been computed and for whom complete data on VMTs are available. The subset of these households for which all household variables are available numbers 8,367. As above, we estimate our models with and without households in the New York urban area.

B. *Characteristics of Vehicle Ownership*

In our sample including New York, approximately 14% of households own no passenger vehicles, 33% own one vehicle, 39% own two vehicles, and 14% own three or more vehicles. The percentage of households owning no vehicles falls to 10% when New York is excluded, and the percentage owning one, two, or three or more increases slightly. Average miles driven per vehicle are highest for two vehicle households (12,264 miles per year; 12,428 without New York), and higher for one-vehicle (11,719 miles; 11,836 without New York) than for three- or more-vehicle households (11,218 miles; 11,260 without New York). The difference in average miles driven per vehicle between one category and the next is, however, only about 600 miles per year. The accords with the fact that the substantial increases in vehicle miles traveled by U.S. households over the last two decades have occurred largely because of increases in the number of vehicles owned rather than in miles driven per vehicle. Finally, the difference in driving habits between the full sample and the sample including the New York urban area is small. Average VMTs per vehicle between the two samples are significantly different only for two-vehicle households.

C. *Models of Vehicle Ownership*

Table 4 presents the vehicle ownership models. The omitted category in each model is "owns no cars." In addition to reporting the multinomial logit coefficients and their standard errors, marginal effects, expressed as elasticities, are calculated for variables having a statistically significant effect on vehicle choice.[20]

The effects of household characteristics on vehicle ownership are largely as expected and agree with the literature. Household size and composition have a significant effect on the number of vehicles purchased, as found by Train (1980, 1986) and Mannering and Winston (1985). These results are robust to the inclusion or exclusion of New York from the sample. White households have a smaller chance of owning no vehicles and larger chances of owning one, two, or three or more vehicles than nonwhite households. When New York is excluded from the sample, black households have a larger chance of owning zero or one vehicle than nonblack households. In general, an additional family member has a larger effect on the probability of owning two vehicles (or three or more vehicles) than does race.

Income and education have small but statistically significant effects on car ownership. Increases in income (net of the fixed costs of car ownership) reduce the probability of a household owning one or no vehicles, but increase the

[20] Marginal effects are calculated as in table 2, by computing the effects of a unit change in race and in the number of family members and of a 10% change in other variables on the probability that a household selects each alternative. These changes are averaged across households.

TABLE 4.—MULTINOMIAL LOGIT MODELS OF VEHICLE CHOICE

	Whole Sample						Excluding New York City					
	1-Car		2-Car		3†-Car		1-Car		2-Car		3†-Car	
	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡	Coeff.†	ε‡
Elderly	−0.030	−23.0	0.526	+16.4	0.618	+20.2	−0.058	−27.6	0.597	+17.6	0.710	+22.3
	(0.42)		(4.84)***		(4.87)***		(0.61)		(4.44)***		(4.83)***	
Working adult males	0.683	−46.4	1.968	+28.0	2.528	+86.8	0.757	−64.5	2.131	+26.6	2.691	+82.3
	(7.95)***		(12.94)***		(15.73)***		(5.13)***		(11.86)***		(13.84)***	
Working adult females	0.493	−36.5	1.416	+14.5	2.084	+89.1	0.654	−41.5	1.715	+16.2	2.369	+85.8
	(3.83)***		(6.20)***		(9.15)***		(4.00)***		(9.45)***		(11.44)***	
Nonworking adults	−0.079	−38.8	0.798	+13.5	1.356	+72.3	−0.160	−42.7	0.801	+13.2	1.366	+71.0
	(0.80)		(8.30)***		(11.20)***		(1.45)		(5.66)***		(8.10)***	
Children aged 17–21	−0.366	−38.9	0.181	−16.8	1.413	+137	−0.227	−39.5	0.360	−18.4	1.666	+144
	(3.02)***		(1.13)		(6.60)***		(1.79)*		(2.06)**		(9.04)***	
Children aged 0–16	0.015	−6.9	0.239	+12.2	−0.015	−12.2	−0.069	−7.4	0.133	+10.7	−0.122	−13.2
	(0.22)		(2.86)***		(0.16)		(1.39)		(2.34)**		(1.74)*	
Log of adjusted income	0.201	−0.3	0.931	+0.2	1.196	+0.4	0.332	−0.3	1.117	+0.2	1.534	+0.5
	(1.94)*		(6.23)***		(4.31)***		(4.95)***		(11.17)***		(11.35)***	
Years of schooling of most educated member	0.167	+0.1	0.207	+0.4	0.193	+0.1	0.186	+0.09	0.221	+0.3	0.199	−0.05
	(8.26)***		(9.97)***		(7.84)***		(8.53)***		(8.21)***		(5.90)***	
White household	1.137	+12.9	1.344	+14.2	1.581	+34.0	0.820	+9.5	0.880	+4.6	1.019	+15.3
	(6.02)***		(4.30)***		(4.10)***		(4.82)***		(4.01)***		(4.27)***	
Black household	−0.140		−0.417		−0.494		−0.536	+4.7	−0.812	−9.2	−0.983	−18.7
	(0.56)		(1.43)		(1.29)		(2.90)***		(3.09)***		(3.08)***	
Annual rainfall	−0.000		−0.004		−0.010		0.001		−0.003		−0.008	
	(0.09)		(0.79)		(1.47)		(0.35)		(0.55)		(1.34)	
Annual snowfall	−0.042		−0.007		−0.024		−0.049		−0.017		−0.035	
	(1.52)		(0.22)		(0.52)		(1.92)*		(0.55)		(0.78)	
Cost of automobile travel per mile	−0.063	+1.1	−0.564	−0.9	−0.606	−0.8	0.139		−0.265		−0.284	
	(0.27)		(1.73)*		(1.76)*		(0.90)		(1.31)		(1.20)	
Road density	1.415		−0.021		−2.142		0.539		−0.911		−3.378	
	(0.17)		(0.00)		(0.23)		(0.06)		(0.12)		(0.36)	
Presence of rail transit	−0.217		−0.240		−0.220		−0.290		−0.299		−0.290	
	(1.46)		(1.42)		(1.03)		(2.38)**		(2.16)**		(1.58)	
Supply of rail transit	−10.862		−11.751		−14.422		−16.825	+0.004	−25.394	−0.01	−29.965	−0.02
	(1.34)		(1.21)		(1.27)		(1.91)*		(2.19)**		(2.01)**	
Supply of bus transit	−17.551	+0.01	−30.347	−0.1	−20.636	+0.04	−17.853	+0.02	−29.338	−0.09	−19.336	+0.05
	(1.76)*		(2.21)**		(1.16)		(1.94)*		(2.38)**		(1.14)	
Population centrality	−9.402	−0.2	−10.569	−0.2	−11.359	−0.2	−9.705	−0.09	−11.462	−0.14	−12.580	−0.2
	(3.45)***		(2.88)***		(2.83)***		(3.41)***		(3.45)***		(3.11)***	
City shape	−0.479		−0.657		−0.763		−0.419	+0.02	−0.610	−0.04	−0.722	−0.09
	(1.31)		(1.55)		(1.61)		(1.34)		(1.72)*		(1.79)*	
Jobs-housing balance	0.149		0.889		0.809		0.238		0.958		0.913	
	(0.23)		(1.08)		(0.76)		(0.42)		(1.39)		(0.94)	
Land area	−0.098	+0.04	−0.199	−0.12	−0.177	−0.05	−0.069	+0.05	−0.163	−0.06	−0.141	−0.01
	(1.66)*		(2.70)***		(2.03)**		(1.49)		(2.75)***		(1.90)*	
Population density	0.578	+0.1	0.701	+0.15	0.496	−0.1	0.610	+0.06	0.709	+0.11	0.492	−0.1
	(2.02)**		(2.23)**		(1.26)		(2.29)**		(2.46)**		(1.32)	
Constant	−1.988		−8.683		−12.765		−4.371		−11.974		−17.522	
	(0.79)		(2.74)***		(2.86)***		(2.96)***		(6.80)***		(7.63)***	
Observations			8367						6878			

* Significant at 10%; ** significant at 5%; *** significant at 1%.
† The column reports the coefficient for the variable and, in parentheses, the z statistic. Standard errors are corrected for heteroskedasticity and clustered at each city.
‡ The column reports elasticity for continuous variables, and the percentage change in probability of choosing the mode in response to a unit change in discrete variables.

probability that it owns two, or three or more, vehicles. An increase in the years of schooling of the most educated household member increases the chances that a household owns one or two vehicles. The fact that the vehicle ownership is inelastic with respect to income agrees with other U.S. studies based on household data (Mannering & Winston, 1985; Train, 1980).

Of our measures of urban form, only population centrality has a significant impact on the odds of car ownership. Households in less sprawled cities (cities with more centralized populations) are less likely to own one vehicle, two vehicles, or three or more vehicles. A 10% increase in population centrality reduces the probability of owning two vehicles by approximately 1.5% and the probability of owning three or more vehicles by approximately 2.1% in both samples. More circular cities reduce the odds of owning two or more vehicles, although the effect is only marginally significant. The effect of jobs-housing balance, by contrast, is never significantly different from 0 at conventional levels, nor is that of road density.

Among measures of transit, a 10% increase in bus supply reduces the odds of owning two vehicles by approximately 1%, whether or not New York is included in the sample. When New York is excluded from the sample, greater rail supply reduces the likelihood of vehicle purchase, conditional on a city having a rail system to begin with.[21]

D. *Models of VMT per Vehicle and Effects on Total VMTs*

Table 5 presents demand functions for VMTs per vehicle, estimated separately for one-, two-, and three or more vehicle households. The selectivity correction term added to each equation is based on table 4. Inasmuch as the dependent variable is the logarithm of VMTs per vehicle, the coefficients in table 5 represent the proportionate change in annual household VMTs corresponding to a 1-unit change in each variable (with the exception of the income variable), holding the household's vehicle stock constant.

The number of persons in a household has a significant effect on annual VMTs per vehicle; however, this effect is generally not as great as the effect of an additional person on VMTs that occurs through vehicle choice.[22] For example, focusing on the results without New York, adding an adult male to a household raises average VMTs by approximately 6,000 miles annually, with most of this effect occurring through vehicle choice (5,000 miles) rather than miles per vehicle (1,000 miles). Adding a working adult female to the household or a young adult aged 17–21 increases driving by approximately 5,000 miles annually. In each case approximately 4,000 miles of this effect occurs through an increase in the number of vehicles owned rather than through an increase in miles driven per vehicle.

Previous studies (Mannering & Winston, 1985; Train, 1986) suggest that income has a small effect on vehicle usage, holding number of vehicles constant. Regardless of the number of vehicles owned, the elasticity of VMTs with respect to income is small, although the income elasticity of annual VMTs is approximately twice as high in one-vehicle households—0.30 without New York—as in two- or three-vehicle households (table 5).

Our sprawl and transit measures have statistically significant effects on miles driven per vehicle primarily in one-vehicle households (table 5). An increase in road density increases annual miles driven by these households, as does a decrease in jobs-housing balance. The more circular a city, the fewer the miles driven by one-vehicle households. In rail cities an increase in rail route miles reduces annual VMTs; however, the magnitude of this effect is sensitive to the inclusion of New York in the sample.

What are the combined effects of our measures of urban form and transit supply on total miles driven annually? The effect of a 10% change in city shape, road density, rail supply (for rail cities), and jobs-housing balance is to change average annual miles driven by at most 0.7% for each variable. Population centrality, which affects average VMTs only through its effect on vehicle choice, has a slightly larger, but still modest, effect. A 1% increase in population centrality reduces average annual miles driven by 1.5% when New York is removed from the sample. As we report elsewhere (Bento et al., 2003), the 10% increase in population centrality in the sample without New York reduces annual average VMTs by approximately 300 miles per year—approximately half the size (in absolute value) of a 10% increase in household income. Individually, the effect of changing measures of urban form and transit supply is small—indeed, smaller than the predicted impact of a change in the gasoline tax on vehicle ownership and miles driven (Mannering & Winston, 1985; West, 2004). This is, however, not necessarily the case if measures of urban form and transit supply are considered jointly.

V. The Effect of Changing All Sprawl and Transit Measures Simultaneously

The results presented above suggest that measures of urban sprawl and transit availability may have modest effects on the commute mode choices and annual VMTs of U.S. households. This is, however, not necessarily the case if several measures of urban form and transit supply change simultaneously. To examine the impact of changing all of our measures of sprawl and transit availability, we predict the vehicle choices and VMTs per vehicle of all households in our sample, assuming that they live in a city with measures of urban form and transit availability identical to those in each of six U.S. cities: Atlanta, Boston, Chicago, Houston, New York and San Diego. We also use the logit model from table 3 to predict the probability that the workers in our sample households will drive to work, for each of the six cities. As a check on the consistency of our results, average commute miles driven are calculated by multiplying the average probability of driving to work by the average number of workers in our sample households (1.04) times the average annual commute length in the 1990 NPTS (approximately 6,000 miles per year). The ratio of average commute miles driven to average VMTs should be approximately one-third, given that work trips account for 34% of annual VMTs in the 1990 NPTS.

[21] Note that equations (2) and (3) include a dummy variable (rail dummy) equal to 1 if a rail system is present and 0 if it is not. Rail supply may therefore be interpreted as the product of rail miles supplied and the rail dummy.

[22] The effect of a variable on annual VMTs can be computed as follows. Let $P_1M_1 + P_2M_2 + P_3M_3$ be the average household miles traveled before a variable is altered, where P_I is the proportion of households owning I vehicles and M_I is the annual average VMTs for households owning I vehicles, $I = 1, 2, 3$. Let primes denote the value of each term after a variable is altered. The change in average annual VMTs, $\sum P_I'M_I^* - \sum P_IM_I$, can be decomposed as $\sum (P_I^* - P_I)M_I + \sum P_I^*(M_I^* - M_I)$, where the first term represents an effect on vehicle ownership and the second an effect on miles traveled per vehicle.

Table 5.—OLS Models of ln(Vehicle Miles Traveled) per Vehicle

	Whole Sample			Excluding New York City		
	1-Car Households	2-Car Households	3-Car Households	1-Car Households	2-Car Households	3-Car Households
Elderly	−0.188	−0.194	−0.024	−0.197	−0.217	0.000
	(2.74)***	(5.44)***	(0.52)	(2.13)**	(6.47)***	(0.00)
Working adult males	0.480	0.071	0.085	0.539	0.056	0.053
	(5.87)***	(1.78)*	(2.11)**	(4.05)***	(1.39)	(1.16)
Working adult females	0.248	−0.011	0.044	0.262	−0.037	0.010
	(3.32)***	(0.22)	(0.96)	(2.15)**	(0.79)	(0.20)
Nonworking adults	0.021	−0.056	0.025	0.086	−0.079	−0.028
	(0.28)	(1.40)	(0.39)	(0.71)	(2.00)**	(0.47)
Children aged 17–21	0.323	0.046	0.165	0.369	0.077	0.122
	(3.62)***	(0.81)	(2.39)**	(2.88)***	(1.29)	(1.65)
Children aged 0–16	0.043	−0.012	−0.041	0.040	−0.023	−0.037
	(1.31)	(0.67)	(1.81)*	(0.99)	(1.36)	(1.42)
Log of adjusted income	0.232	0.126	0.134	0.299	0.123	0.121
	(3.54)***	(3.73)***	(2.97)***	(4.70)***	(3.13)***	(1.93)*
Years of schooling of most	0.042	0.028	0.031	0.031	0.028	0.034
educated member	(3.44)***	(5.05)***	(2.45)**	(2.90)***	(4.45)***	(2.39)**
White household	0.063	0.078	−0.024	−0.023	0.073	−0.055
	(0.59)	(1.34)	(0.29)	(0.21)	(1.09)	(0.59)
Black household	−0.096	−0.080	0.010	−0.198	−0.108	−0.001
	(0.69)	(0.81)	(0.08)	(1.49)	(0.96)	(0.01)
Annual rainfall	0.003	0.001	0.002	0.003	0.001	0.002
	(1.34)	(0.63)	(0.74)	(1.25)	(0.78)	(1.03)
Annual snowfall	−0.007	−0.009	0.008	−0.011	−0.009	0.010
	(0.31)	(1.47)	(0.50)	(0.47)	(1.42)	(0.56)
Cost of automobile travel	0.012	0.012	−0.081	0.056	0.023	−0.070
per mile	(0.14)	(0.19)	(0.80)	(0.61)	(0.33)	(0.63)
Road density	6.954	1.014	0.734	6.632	1.099	1.141
	(2.30)**	(0.70)	(0.26)	(2.16)**	(0.75)	(0.41)
Presence of rail transit	−0.031	0.043	−0.026	−0.026	0.034	−0.054
	(0.41)	(1.18)	(0.38)	(0.35)	(0.98)	(0.75)
Supply of rail transit	−5.160	−4.702	−1.046	−9.281	−3.366	2.929
	(1.35)	(2.32)**	(0.32)	(1.69)*	(0.78)	(0.45)
Supply of bus transit	−4.148	−3.150	−6.210	−3.091	−3.112	−7.248
	(0.85)	(0.82)	(0.85)	(0.59)	(0.78)	(0.92)
Population centrality	1.899	−0.036	−0.389	1.503	0.076	−0.029
	(1.28)	(0.04)	(0.28)	(0.98)	(0.09)	(0.02)
City shape	−0.275	0.093	−0.240	−0.286	0.096	−0.233
	(2.15)**	(0.80)	(1.33)	(2.23)**	(0.83)	(1.30)
Jobs-housing balance	0.762	0.324	0.204	0.734	0.336	0.250
	(1.66)*	(1.43)	(0.69)	(1.64)	(1.50)	(0.80)
Population density	−0.077	−0.020	0.104	−0.092	−0.020	0.116
	(0.60)	(0.28)	(0.75)	(0.73)	(0.27)	(0.82)
Land area	0.000	0.017	−0.002	0.002	0.020	0.003
	(0.01)	(0.97)	(0.08)	(0.08)	(1.20)	(0.11)
Selectivity correction factor	0.091	0.007	−0.023	0.096	0.019	−0.006
	(3.37)***	(0.33)	(1.12)	(2.22)**	(0.97)	(0.27)
Constant	5.334	7.163	7.408	4.730	7.195	7.529
	(4.87)***	(12.47)***	(8.32)***	(4.30)***	(11.90)***	(7.16)***
Observations	2762	3247	1208	2296	2824	1048
R^2	0.11	0.07	0.04	0.12	0.08	0.04

t-Statistics in parentheses. Standard errors are corrected for heteroskedasticity and clustered at each city.
* Significant at 10%; ** significant at 5%; *** significant at 1%.

The results of our experiment appear in table 6.[23] Several results stand out. The probability of driving to work is lowest in the oldest three cities in the table—New York (0.40), Boston (0.73), and Chicago (0.74), each of which has an extensive rail and bus system. The probability of driving is highest in Houston (0.90), which has no rail system and the highest road density of the six cities. The predictions of commuting behavior are in line with our predictions of total household VMTs—average commute miles driven range from 26% of annual VMTs in New York to 36% of annual VMTs in Houston.

The effects of all measures of urban form and transit supply on average household VMTs are striking. If the households in our sample were to live in a city with measures of urban form identical to those in Atlanta, average annual

[23] The calculations in table 6 are based on the models in tables 3, 4, and 5 that include New York. Using the models excluding New York alters predictions of average annual VMTs by at most 2%. Using the logit model estimated without New York lowers the predicted probability of driving to work by 1–2 percentage points.

TABLE 6.—IMPACTS ON DRIVING OF MOVING OUR SAMPLE HOUSEHOLDS TO VARIOUS METROPOLITAN AREAS

Urban Area	Minimum	Maximum	Atlanta, GA	Boston, MA	Chicago, IL	Houston, TX	New York, NY	San Diego, CA
Lane density (area of roads per 100 square miles of land)	1.6	10.6	3.9	4.3	4.7	5.2	5.3	4.2
Land area (km^2)	135	7,683	2,944	2,308	4,104	3,049	7,683	1,788
Population	158,553	16,044,012	2,157,806	2,775,370	6,792,087	2,901,851	16,044,012	2,348,417
Density (people per square kilometer)	446	2,240	733	1,202	1,655	952	2,088	1,314
Presence of rail transit	0	1	1	1	1.0	0	1	1.0
Rail transit supply (10,000 mi/km^2)	0	5.7	0.7	1.8	1.9	0.0	5.7	0.2
Nonrail transit supply (10,000 mi/km^2)	0.1	4.3	1	1.3	2.75	1.42	3	1.64
Jobs-housing balance	0.115	0.58	0.443	0.284	0.35	0.44	0.412	0.58
Population centrality	0.114	0.218	0.114	0.171	0.15	0.13	0.197	0.20
City shape	0.038	0.994	0.264	0.816	0.48	0.80	0.727	0.36
Predicted average annual vehicle miles traveled per household			16,899	12,704	14,408	15,685	9,453	16,493
Predicted average probability of driving to work by workers			0.87	0.73	0.74	0.90	0.40	0.84
Predicted average commute miles driven			5,450	4,565	4,620	5,641	2,496	5,247

VMTs per household would equal 16,899.[24] This number drops to 12,704 miles annually if the households in our sample move to a city with urban form and transit supply variables identical to Boston—a reduction in annual VMTs of 25%. This result is driven by differences in public transit supply, in city shape, and, especially, in population centrality between the two cities. Atlanta is almost 2 standard deviations below the mean of all 114 cities in population centrality, whereas Boston is 0.66 standard deviations above the mean. Jobs-housing balance is also greater in Boston than in Atlanta. When we move the households in our sample to New York, the effect is even more striking—average annual VMTs per household fall to 9,453. This is the result of large differences in population centrality between Atlanta and New York (New York is almost two standard deviations above the mean for all U.S. cities), and of differences between the two cities in the supply of public transit, especially rail transit. Annual VMTs in Chicago (14,408)—the highest of our three older cities—are still 8% below annual VMTs in a city with the characteristics of Houston and 15% below annual VMTs in Atlanta.

VI. Conclusions

Our results suggest that individual measures of urban form and public transit supply have a small but statistically significant effect on travel demand. For example, a 10% increase in population centrality lowers the chance that a worker drives to work by 1 percentage point. The effects of a 10% change in rail and bus miles supplied are approximately half as large. Urban form and transit supply affect annual miles driven by influencing both the number of cars owned and the miles traveled per vehicle. In cities where the spatial distribution of population is more compact, households are less likely to own a car. The quantitative effect of these variables on annual average VMTs is, however, small: a 10% increase in population centrality, through its effect on vehicle choice, reduces annual VMTs by only 1.5%. Other measures of urban form and transit supply—jobs-housing balance, road density, city shape, and the supply of rail transit—all affect the average miles driven per vehicle but not the number of vehicles owned. The elasticity of annual VMTs with respect to each of these variables is less than 0.1 in absolute value.

The results presented above suggest that measures of urban sprawl and transit availability may have only modest effects on the commute mode choices and annual VMTs of U.S. households. This is, however, not necessarily the case if several measures of urban form and transit supply change simultaneously. To examine the potential for such measures we use the models of vehicle ownership and miles driven to predict the annual miles that each of our sample households would drive if they were to live in a city with the same measures of urban form and transit supply as six U.S. cities (Atlanta, Boston, Chicago, Houston, New York, and San Diego). We perform a similar exercise for commuters to predict the probability of driving to work. This exercise suggests that measures of urban form and transit supply—taken together—have a significant effect on travel demand. The effect of moving our sample households from a city with measures of urban form and transit supply the same as

[24] Formally, we calculate $(1/N)\sum_i \sum_j P(i, j) M(i, j)$, where $P(i, j)$ is the predicted probability that household i purchases vehicle bundle j, and $M(i, j)$ is the number of miles the household is predicted to travel conditional on owning bundle j.

to those of Atlanta to a city with measures the same as those of Boston is to reduce annual VMTs by 25% and the average probability of driving to work from 0.87 to 0.73.

Our results should however be interpreted with caution for at least two reasons. First, our sprawl measures could be capturing aspects of cities that are correlated with our measures of urban form but are different from them. (For example, a city with extensive bus routes may have good sidewalks.) Second, there is a large gap between the measures of urban form in our models and policies to alter urban form: it may take several years until measures that change urban spatial structure produce any real effect. Nonetheless, our study suggests that, even in a country like the U.S. that is heavily dependent on the automobile, urban form does affect travel demand.

REFERENCES

Badoe, Daniel, and Eric J. Miller, "Transportation–Land Use Interaction: Empirical Findings in North America, and Their Implications for Modeling," *Transportation Research Part D* 5 (2000), 235–263.

Bento, Antonio M., Maureen L. Cropper, Ahmed Mushfiq Mobarak, and Katja Vinha, "The Impact of Urban Spatial Structure on Travel Demand in the U.S.," World Bank policy research working paper no. 3007 (2003).

Bento, Antonio M., and Sofia Franco, "The Costs of Anti-Sprawl Policies," *Journal of Urban Economics* (forthcoming).

Boarnet, Marlon G., and Randall Crane, "The Influence of Land Use on Travel Behavior: Specification and Estimation Strategies," *Transportation Research Part A* 35:9 (2001), 823–45.

Boarnet, Marlon G., and Sharon Sarmiento, "Can Land Use Policy Really Affect Travel Behavior? A Study of the Link between Non-eork Travel and Land Use Characteristics," *Urban Studies* 35:7 (1998), 1155–1169.

Brueckner, Jan K., "Urban Sprawl: Lessons from Urban Economics," Brookings-Wharton papers on urban affairs (2001).

Crane, Randall, and Richard Crepeau, "Does Neighborhood Design Influence Travel? A Behavioral Analysis of Travel Diary and GIS Data," *Transportation Research Part D* 3 (1998), 225–238.

Dubin, Jeffrey, and Daniel McFadden, "An Econometric Analysis of Residential Electric Appliance Holding and Consumption," *Econometrica* 52:2 (1984), 53–76.

Galster, George, Royce Hanson, Michael Ratcliffe, Harold Wolman, Stephen Coleman, and Jason Freihage, "Wrestling Sprawl to the Ground: Defining and Measuring and Elusive Concept," *Housing Policy Debate* 12:4 (2000), 681–717.

Glaeser, Edward, and Mathew E. Kahn, "Decentralized Employment and the Transformation of the American City," NBER working paper no. 8117 (2001).

Goldberg, Pinelopi K., "The Effects of the Corporate Average Fuel Efficiency Standards in the U.S.," *Journal of Industrial Economics* 46:1 (1998), 1–33.

Kahn, Mathew, "The Environmental Impact of Suburbanization," *Journal of Policy Analysis and Management* 19:4 (2000), 569–586.

Levinson, D. M., and A. Kumar, "Density and the Journey to Work," *Growth and Change* 28:2 (1997), 147–172.

Malpezzi, Stephen, "Estimates of the Measurement and Determinants of Urban Sprawl in U.S. Metropolitan Areas," University of Wisconsin mimeograph (1999).

Mannering, Fred, and Clifford Winston, "A Dynamic Empirical Analysis of Household Vehicle Ownership and Utilization," *Rand Journal of Economics* 12:2 (1985), 215–236.

Massey, Douglas, and Nancy Denton, "The Dimensions of Residential Segregation," *Social Forces* 67:2 (1988), 281–315.

McDonald, John, "Econometric Studies of Urban Population Density: A Survey," *Journal of Urban Economics* 26:3 (1989), 361–85.

McFadden, Daniel, "The Measurement of Urban Travel Demand," *Journal of Public Economics* 3 (1974), 303–328.

Mieszkowski, Peter, and Edwin Mills, "The Causes of Metropolitan Suburbanization," *Journal of Economic Perspectives* 7:3 (1993), 135–147.

Mills, Edwin, "The Measurement and Determinants of Suburbanization," *Journal of Urban Economics* 32:3 (1992), 377–387.

Muth, Richard E., *Cities and Housing. The Spatial Pattern of Urban Residential Land Use* (Chicago: The University of Chicago Press, 1969).

Newman, Peter, and Jeffrey Kenworthy, *Cities and Automobile Dependence: An International Sourcebook* (Aldershot: Gower, 1989).

Sarmiento, Sharon, "Household, Gender and Travel," in *Proceedings from the Second National Conference on Women's Travel Issues* Federal Highway Administration (2000).

Train, Kenneth, "A Structured Logit Model of Auto Ownership and Mode Choice," *Review of Economic Studies* 47:2 (1980), 357–370.

——— *Qualitative Choice Analysis* (Cambridge, MA: MIT Press, 1986).

U. S. Department of Transportation, Federal Highway Administration, *Nationwide Personal Transportation Survey* (Washington DC, 1990).

Walls, Margaret, Winston Harrington, and Alan Krupnick, "Population Density, Transit Availability and Vehicle Travel: Results from a Nested Logit Model of Vehicle Choice and Use," Resources for the Future mimeograph (2000).

West, Sarah, "Distributional Effects of Alternative Vehicle Pollution Control Policies," *Journal of Public Economics* 88 (2004), 735–757.

Wheaton, William C., "Land Use and Density in Cities with Congestion," *Journal of Urban Economics* 43:2 (1998), 258–272.

White, Michael J., "Segregation and Diversity: Measures in Population Distribution," *Population Index* 52 (1986), 198–221.

White, Michelle, "A Model of Residential Location Choice and Commuting by Men and Women Workers," *Journal of Regional Science* 17:1 (1977), 41–52.

——— "Sex Differences in Urban Commuting Patterns," *American Economic Review* 76:2 (1986), 368–372.

——— "Location Choice and Commuting Behavior in Cities with Decentralized Employment," *Journal of Urban Economics* 24:2 (1988), 129–152.