Deconstructing development density:
Quality, quantity and price effects on household non-work travel

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Abstract (212 words)

Smart growth and transit-oriented development proponents advocate increasing the density of new land development and infill redevelopment. This is partly in order to reduce auto use by reducing distances between trip origins and destinations, creating a more enjoyable walking environment, slowing down road travel, and increasing the market for transit. But research investigating how development density influences household travel has typically been inadequate to account for this complex set of hypotheses: it has used theoretically unjustified measures, has not accounted for spatial scale very well, and has not investigated potentially important combinations of measures. Using data from a survey of metropolitan households in California, measures of development density corresponding to the main hypotheses about how density affects travel—activity density affecting distance traveled, network load density affecting the speed of auto travel, and built form density affecting the quality of walking—are tested as independent variables in models of auto trip speed and individual non-work travel. Residential network load density is highly negatively correlated with the speed of driving, and is in turn highly positively correlated with non-work travel, both singly and in combination with other measures. Activity density and built form density are not as significantly related, on their own. These results suggest that denser development will not influence travel very much unless road level-of-service standards and parking requirements are reduced or eliminated.

Keywords: Development density; travel behavior; congestion; road level-of-service standards; built environment; transit-oriented development

1 Introduction

The reliance of American households on their cars has received increasing political attention as urban congestion has worsened, commute durations have risen, air quality has deteriorated, and the prospect of global climate change has become more definite. In response, planning academics and practitioners have often recommended policies intended to slow or reverse "sprawl" and thus, it is hoped, to decrease auto use. Household travel decisions may indeed be influenced by built environment factors such as the distance to shops and services, the structural density of buildings, transit access, and freeway capacity. But there is considerable scholarly disagreement about the nature and magnitude of such influences (Badoe and Miller 2000; Boarnet and Crane 2001b), despite more than a hundred empirical studies on the topic (Crane 2000; Ewing and Cervero 2001). One explanation for the mixed findings within the empirical literature is the lack of a clear rationale for choosing built environment measures. Development density is a central example. It is typically measured as gross population density, and sometimes as gross employment density, partly for convenience and partly guided by precedent. Pushkarev and Zupan (1977) may have initiated the tradition in their seminal study of rail and bus system performance in the New York metropolitan area, finding a strong relationship between the number of residents per gross land area and transit ridership. But the gross population density measure, problematic even in predicting markets for transit commuting, is less sensible still as a basis for understanding either non-work travel or travel by non-transit modes. Segregated residential areas have higher gross population density *ceteris paribus*, as well as possibly having less frequent transit service, fewer activities within walking distance, wider streets, and more ample parking. Gross population density may or may not be correlated with congestion, the availability of activities, or the quality of the walking environment in any given metropolitan area or sub-area, in part due to variance in the era of development, current and historical land use policies, road network capacity, and the regional economy.

Aggregate studies of household travel using cities or sub-metro areas as units of analysis have generally found an inverse relationship between development density (typically measured as gross population density) and auto use (Dunphy and Fisher 1996; Kockelman 1995; Newman and Kenworthy 1999). Other recent controlled studies have found a strong correlation between urban area population density and area-wide measures of congestion (Hahn et al. 2002; Sarzynski et al. 2006). Aggregate analyses focusing on smaller areas, such as employment sites, Census tracts, and sub-cities, have generally also found correlations between gross employment or population density, higher alternative mode use, lower auto use, or lower auto ownership (e.g., Cervero 1988; Dunphy and Fisher 1996; Holtzclaw 1994; Messenger and Ewing 1996). Some of these aggregate analyses have controlled for transportation capacity measures such as freeway supply, transit supply, and freeway congestion (e.g., Cervero 1989; Hahn et al. 2002; Sarzynski et al. 2006), but because cities are likely heterogeneous along unobserved dimensions that correlate with observed variables, these analyses may not be sufficiently controlled.

Studies using disaggregate data about individual or household travel are better able to account for heterogeneity within and between places, but such studies also have typically relied on gross population or employment density measures that may function as proxies for several unobserved correlates. These studies have sometimes found statistically significant relationships between measures of household travel and gross employment density, gross population density, or a combination of both (e.g., Boarnet and Greenwald 2000; Boarnet and Sarmiento 1998; Crane and Crepeau 1998; Ewing 1995; Frank and Pivo 1994). However, the disaggregate studies have mixed results in comparison to aggregate studies. In some cases other land use measures (e.g., accessibility indexes) are more significant in controlled models, and the density measures are either not significant or of arguably marginal significance (Ewing et al. 1996; Kockelman 1995; Levinson and Kumar 1997; Pickrell and Schimek, as reported in Pickrell 1999; Schimek 1996; Sun et al. 1998).

Gross population density is the standard measure, but in fact measuring development density presents a complex set of choices (Churchman 1999):

different numerators (e.g., structures, population, employment by type, roads), different divisors (e.g., gross land area, land area net of roads and parking, developed land area, land area by development type, transportation network capacity), and scales ranging from the Census block to the metropolitan area. Choosing from this potential set of measures should be systematic rather than based on convenience, as different density types can be expected to have qualitatively and quantitatively different effects on available travel choices.

Even methodologically sophisticated and recent research has tended to use population density or net residential density in an *ad hoc* fashion, either to represent several hypothesized effects simultaneously or merely as a control variable without clear justification (e.g., Boarnet and Greenwald 2000; Frank et al. 2004; Giuliano and Narayan 2003; Naess 2006; Schimek 1996). And though smaller areas are likely to matter more for non-motorized travel than for auto and bus travel, only recently has there been any systematic attention paid to scale when measuring the built environment’s relationship with different modes of travel (Zhang and Kukadia 2005). Finally, most disaggregate research has generally not attempted to account for correlates of development density such as transit service and road supply, which are likely to vary considerably within and across cities.

This study addresses these problems by testing the relationship between personal travel and a set of development density measures that is specified in order to explicitly account for the most important hypothesized influences on travel; accounting both for scale and for interactions among density measures. The data come from an original household travel survey carried out in the San Diego and San Francisco-Oakland-San José metropolitan areas. Measures of travel include auto speed, the number of non-work trips by mode, and non-work vehicle miles traveled. These variables are of interest because of the growing amount of non-work travel (81 percent of trips and 73 percent of distance traveled in the most recent nationwide survey of travel, the 2001 NHTS (Hu and Reuscher 2004)); the negative congestion, pollution, and greenhouse gas impacts of auto use; and the potential for other modes to substitute for the auto.

This study, while not attempting to estimate a simultaneous system accounting for travel as part of the consumption choices of households (see, e.g., Anas 2007), nevertheless helps to provide evidence about which sorts of influences may be most important, and thus which built environment characteristics deserve more research attention.

2 Analytic Framework and Research Hypotheses

Via what mechanisms does development density influence travel choices? At what scale should measures be taken? How do these influences interact to affect modal substitution? Below I describe this tripartite "deconstruction" of development density —by type, by scale, and by interaction—and list seven corresponding hypotheses (numbered H1 to H7).

2.1 Density by type: Quality, quantity and price

When people engage in activities outside the home and workplace, they face time and money constraints that affect how frequently and for how much time they can engage in those activities, and they experience travel itself as both an activity and as an integral part of that decision making process. The built environment, and in particular, development density of different types, seems likely to influence (a) the *quality* of the travel experience, particularly walking, (b) the *quantity* (distance) of travel required to access activities, and (c) the per-unit *prices* of travel, in time and money, consistent with standard utility maximization frameworks and household production theory (Becker 1965) (see Appendix).

Quality. To some extent household travel is purely instrumental. People get places by traveling, and so travel has been called a "derived demand." But traveling is also an activity, experienced qualitatively, which is more or less pleasurable or onerous depending on the mental and physical effort required, visual and aesthetic characteristics along the chosen route, exposure to weather and pollution, and considerations of privacy and interaction with others. Development density has a role to play in the quality of travel because people may enjoy walking in places with dense built form, where buildings come right up to the sidewalk and there is a minimum of empty lots and surface parking

(Duany et al. 2000; Jacobs 1961; Untermann 1984). Places with dense built form may also be more likely to have wide sidewalks, street trees, and shops oriented towards pedestrians, partially because there are economies of scale in the provision of such amenities that are realized by the crowding together of structures. Thus **built form density** is defined as the density of structures on developed land, which is hypothesized to improve the quality of the walking environment and thus increase walking frequency.

Quantity. The distance from home, work, or school to other activities affects the quantity of travel needed to get there. Development density may reduce distances between activities, simultaneously making it possible for people to spend less time traveling, and making walking and bicycling significantly easier. Thus **activity density** is defined as the number of local desirable non-work activities.[1] But its effects are theoretically ambiguous *ceteris paribus*. People might respond to shorter distances by increasing activity frequency and auto trip making (Crane 1996), and they will often pass up closer opportunities for farther-away ones (Handy and Clifton 2001), particularly given the declining real cost of auto ownership, easily traveled roads, and ample parking supply.

[1] If activity locations are scattered randomly within a given radius around a person's home, the expected average distance from home to any activity location remains the same when activity density increases. However, the expected minimum distance gets shorter. Higher local density also implies lower average distance to activities over all activities in the choice set, holding the number of farther-away activities constant.

Price. Presumably the lower the speed of a given mode is—that is, the higher its time price is—the lower the probability of traveling via that mode. **Network load density**, defined as the number of potential local transportation system users per unit of transportation network capacity, may slow down travel by concentrating users on the network, increasing congestion. Slowing may also occur if traffic controls are imposed more restrictively in higher density places with more traffic. The clearest example of this is autos on the road network. Bus travel is also likely to be slow in dense environments, but this effect could be mitigated if in those places transit agencies provide shorter bus headways (reducing waiting time), exclusive right-of-way service such as typical fixed rail systems (increasing in-vehicle speed), and/or higher route density and stop density (reducing walking time) (Kerin 1992; Mohring 1972; Nash 1988). Densely trafficked places may also have scarcer and higher-priced parking, making auto ownership and use more expensive in money terms as well as time to walk to and from the parked car.

Summarizing the discussion above, these three density types are hypothesized to have the following direct relationships with measures of travel via their effects on quality, quantity and price:

> **H1. Type: Built form density.** Built form density is positively correlated with the frequency of walk/bike-access activities and to a lesser extent, transit-access activities.

> **H2. Type: Activity density.** Activity density does not have a strong relationship with activity frequency by mode when controlling for other density types.

> **H3. Type: Network load density.** Network load density is negatively correlated with auto speed and frequency of auto-access activities, controlling for other density types.

2.2 Spatial scale

Characteristics of auto, transit and non-motorized travel are affected by the built environment at different spatial scales. Measures should ideally be made at those scales rather than using arbitrarily sized zones such as Census tracts. Development density measures at larger scales are more appropriate for the motorized modes because they are ordinarily much faster than walking and biking. Analysis can account for this by employing development density measures at different scales and exploring cross-elasticity of demand for activity participation across different travel modes.

> **H4. Scale: Direct effects.** Density at small-scale radii around work and home (e.g., 1/4 or 1/2 mile) have their most direct effects on walk/bike-access activities, while those measured at larger radii (e.g., one and three miles) are more directly influential on auto-access activities and auto mileage.

> **H5. Scale: Indirect effects.** Density types measured at the smaller scale affect auto-access activity frequency and auto mileage via substitution from auto travel; when measured at the larger scale, they indirectly affect walk/bike-access activity frequency. These effects are weaker than the direct effects because modes are imperfect substitutes.

2.3 Interactions of density measures

Perhaps alternative modes become preferred to auto travel only when conditions align, for example, when auto travel is inconvenient and transit travel is easy. If so, failing to investigate such interactions in analysis will yield misleading results. This is not a new observation. Messenger and Ewing (1996) argued that “explanatory variables have been treated as independent when, in fact, they almost certainly have combined effects on transit ridership... Improvements in transit service may have little effect in automobile-rich areas but a large effect in automobile-poor ones.” Rather than explicitly testing hypotheses about important interactions, however, Messenger and Ewing use stepwise regression, while other researchers have represented synergistic combinations of land use features with indices constructed via factor analysis or a more arbitrary process (e.g., 1000 Friends of Oregon 1993). Boarnet and Crane (2001b) criticize the use of such methods for not accounting for the independent effects of land use characteristics and making policy implications explicit. Two main hypotheses are investigated here:

> **H6. Interactive effects: Auto travel.** Network load density’s negative correlation with auto use is strongest when nearby activity density is also high, enabling subsitution.

> **H7. Interaction: Non-motorized travel.** High levels of activity density, built form density, and network load density in combination have larger and more significant correlations with walk/bike travel than they do individually.

3 Methods

3.1 Survey and other data

A computer-aided telephone survey was administered between November 2003 and April 2004 to a random stratified sample of households living in the three core counties of the San Francisco-Oakland-San Jose metropolitan area (Alameda, San Francisco and Santa Clara Counties) and the San Diego metropolitan area. The design included an over-sample of households living within 0.4 miles of twelve selected rail stations in the two metropolitan areas (for details on station area selection see Chatman (2005: 199-217)). The questionnaire collected travel, demographic, and socioeconomic data, including 24 hours of complete activity information. Street addresses or cross streets of home, work, and other activity locations were collected as well, geocoded in post-processing, used to create built environment measures.

The interview was completed by 1,113 adults. Average interview time was 25 minutes, with 10 percent of the sample requiring more than 40 minutes. Response rates for the four telephone-accessible substrata were calculated at between 20 and 24 percent, based on the Council of American Survey Research Organization standards. The completion rate for households in the station areas without known telephone numbers (completions divided by residential addresses) was about seven percent, including vacant units and bad addresses. The low response rates present a concern for the representativeness of the sample for population description purposes, but a substantially less significant concern for the validity of the comparative analysis among subgroups that is presented here (see, e.g., Groves 1989, p 5). The data were to be used primarily in carrying out statistical tests of the differences between subgroups of people, rather than on describing average characteristics of groups, and sociodemographic characteristics are controlled in modeling.

Exactly 1,000 respondents provided information enabling their homes to be geocoded; this is the subset of individuals used for analysis of activity frequency. The vehicle mileage analysis is restricted to 527 of these respondents, due to incomplete reporting of origins and destinations for auto trips.

For the speed analysis, auto trips with complete origin and destination information are used. There are 3,729 trips in the original data set (about 3.4 trips per respondent), of which 51 percent (1,910 trips) have complete origin and destination information. Other data cleaning criteria (e.g., omitting zero-duration, multiple-segment trips) bring the usable number down to 1,597. Of these auto trips make up 80 percent, for a subset size of 1,284 trips for the speed models.

More details on the survey and dataset are available in Chatman (2005: 171-198).

3.2 Measures

Characteristics of the dependent and independent variables appear in Table 1 and Table 2, and are described below.

[Table 1, Table 2]

3.2.1 Dependent variables

Auto speed. Speed is calculated by dividing straight-line auto travel distance (using using geocoded trip origins and destinations) by reported travel duration. The distance calculation uses a formula accounting for the earth's curvature. The mean straight-line reported speed of the trips used in the analysis is about 16.5 kph (10.3 mph) and the median is 14.1 kph (8.7 mph).[2]

Non-work activities. Respondents were asked to provide destination type for all activities during a 24-hour period. They provided information for about 80 percent of activities outside work, home, or school. An out-of-home activity was classified as a non-work activity if it was conducted anywhere outside the home and not at another person's home, at a transit stop, at a parking lot, or at some other location used as a pickup point. Such activities made up 83

[2] While auto speed is more accurately measured assuming shortest network based distance, there is no reason to believe that speed measurements using as-the-crow-flies distance will be systematically biased up or down. It is reasonable to assume that they will be inaccurately measured, but randomly so, leading to increased standard errors in the model described below, but not biased estimates. Also, all trips used in the auto speed model are relatively short, between 1/2 mile and 5 miles in length. Finally, as noted in section 3.3.1 (below), I correct for route directness in the auto speed model with a variable accounting both for the distance of the trip (enabling more direct routes, all else equal, as well as potentially a higher average speed) and intersection density (which at higher levels should allow shorter routes).

percent of those carried out outside home, work, or school. Non-work activities are categorized into three mutually exclusive classes based on mode of access: auto, including motorcycle; transit—i.e., bus and rail; and walking or biking. For segmented trips, mode is assigned to the trip based on the longest-duration segment.

About 40 percent of respondents did not engage in a non-work activity outside the home on the survey day. The average number of trips to access non-work activities was 1.24, 36 percent of the average total number of trips of 3.42 (which include return trips home). Auto and other personal vehicles accounted for 77 percent of non-work trips.

Vehicle miles traveled. Cumulative auto mileage is estimated by adding together straight-line distances traveled to access non-work activities by auto. Distances are calculated as explained above. Return trips are not included. Mileage information for about half of respondents is incorrect due to incomplete reporting of activity locations. The 542 households (54 percent of completed interviews) with non-missing origin and destination (OD) information for all of their trips average significantly fewer trips (3.0) than those lacking some OD information (4.1), though an insignificantly smaller number of total activities including at-home activities and multiple activities at other locations (12.8 vs. 13.2). Among this subset, the average straight-line, one-way distance to access all non-work activities via auto on the survey day was about 3.6 mi. This includes travel on the way to or from other activities such as work.

3.2.2 Independent variables

Built form density is measured by summing the estimated number of residents and employees within a given radius of home and dividing by developed acreage within that radius. Activity density is measured as the number of retail employees within a given radius of home. Network load density is measured in four ways: residents, workers, retail workers, and service workers divided by cumulative road length.[3]

All built environment measures were calculated using ArcView and ArcGIS geographical information system software with electronic parcel, Census block, transportation analysis zone, and street maps.[4] Many of them used airline buffers of one-quarter, one-half, one- and three-mile radii around the geocoded home, work and school locations of respondents. The length of streets and

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[3] The datasets used in the auto speed and activity frequency models are different, which is why the descriptive statistics for the residential network load density measure are different in Table 1 and Table 2.

[4] Street data come from the January 2004 update of the Dynamap street files for California licensed by Geographic Data Technology to the California Department of Transportation. Census 2000 blocks were used for residential population. Employment and acreage by land use for the Bay Area came from the 1454-zone transportation analysis zone (TAZ) file from the San Francisco Bay Area Metropolitan Transportation Commission, updated to 2003 using straight-line imputation between the 2000 and 2005 figures from the Projections 2002 file from the Association of Bay Area Governments. Employment for San Diego was from the 4,000-plus TAZ system for the county maintained by the San Diego Association of Governments (SANDAG). Acreage by land use for San Diego came from the 2004 update of the electronic parcel-level land use map maintained by SANDAG.

number of intersections falling within the buffers were summed. Population, employment and acreage by land use type within the buffers were estimated based on the percentage of the area of the zones falling within each of the buffers. Because the Bay Area transportation analysis zones are relatively large and the spatial distribution of employment is likely to be non-uniform, employment near Bay Area households was estimated using the percentage of the street network of each zone falling within the buffer, rather than land area. The land use file was used to estimate retail and services employment for the San Diego buffers.

The remaining independent variables vary by model type, are listed in Table 1 and Table 2, and are explained in context of the model specifications below.

3.3 Analytic plan and model specification

Two levels of analysis are conducted. First, the calculated speed of auto trips taken by respondents is modeled as a function of network load density measures along with control variables, consistent with the engineering literature on road congestion. Second, both the number of non-work[5] trips and non-work

[5] *Non-work* trips are modeled as the dependent variable for three reasons. First, households are more likely to be sensitive to differences in the quality, quantity and prices of travel to access non-work activities; demand for the commute trip is somewhat inelastic. Second, most household travel is for non-work purposes . Third, investigating work travel in particular is problematic because many households choose home locations based on their anticipated commute, casting doubt on causal inferences about the built environment and commute mode choice (also see note on residential self-selection in section 3.3).

auto mileage are modeled as conventional microeconomic demand functions of variables representing household tastes, time and money budget constraints, and (time) prices of accessing out-of-home activities. The three density measures—built form density, activity density, and network load density—are included in these individual-level travel models. Auto trip speed, is of course, highly correlated with travel measures such as trips and VMT; we expect that lower speeds cause people to drive less frequently and in some cases less far. While not modeling the several variables of interest using a simultaneous equations approach, the approach here does use models that are reduced form models via the utility framework, and that incorporate both direct and indirect influences on auto speed, trip frequency and VMT, as explained below.

Another caveat of the analytical approach described in sections 3.3.2 and 3.3.3 (below) is that it treats travel as an end of consumption rather than attempting to model it as an outcome of daily activity patterns as done in the activity modeling literature (see, e.g., Ben-Akiva and Bowman 1998; Bhat and Koppelman 1999; Gliebe and Koppelman 2002; Golob 1998; Kitamura 2001; Waddell et al. 2002). Activity scheduling is not the focus of the current study, which focuses on different measures of the built environment and how those measures compare to past results using conventional (non-activity-based) models of travel behavior that focus on residential characteristics. Including workplace measures would be another useful addition. However, this would truncate the dataset significantly because many people do not work out of the home at all, or did not work on the day they were surveyed.

An important control problem in any analysis of how the built environment influences travel is the question of residential self-selection. If, for example, people who like to walk to the store choose densely developed neighborhoods with many shops, then unobserved travel preferences may be correlated with characteristics of people's neighborhoods, leading to overestimates of the built environment's independent effects on travel (e.g., Badoe and Miller 2000; Bento et al. 2001; Boarnet and Crane 2001b; Schimek 1996). In other work with this dataset, I explicitly test for this potential bias and find it relatively unimportant in this case: coefficient estimates are largely unaffected (see Chatman 2005).

Like this study, previous research by Boarnet, Crane and co-authors has decomposed the effects of the built environment on the speed and distance of travel (Boarnet and Crane 2001a; Boarnet and Greenwald 2000; Boarnet and Sarmiento 1998; Crane and Crepeau 1998). Using instrumental variables, predicted distances and speeds of auto trips were estimated based on observed auto trips for each respondent, and used as exogenous explanatory variables in models of auto trip making.

The modeling strategy employed here solves several methodological problems of the Boarnet-Crane approach. First, all non-segmented auto trips are used in the speed model, including trips for any purpose, rather than the average non-work trip speed; and in the models of travel behavior, all observations are used, rather than just those households who travel for non-work purposes on the day of the survey. Using only observed trip speeds or respondents with at least one non-work trip truncates the sample, introducing bias and significantly reducing sample size. Second, activity density is used as a measure of the average distance to activities, rather than observed median travel distance, which is an endogenous dependent variable. Finally, trip speed is modeled as a function of built environment measures near the trip origin, destination, or both, rather than at the home location even in cases where the trip does not start or end at home.

3.3.1 Analysis 1: Road speed

Average auto speed on a road network has been shown to be an exponentially decreasing function of “traffic density,” the number of autos on a segment of road divided by its length (Small 1992: 69, eq. 3.22). Because contemporaneous data on traffic volume and density are not available, these fundamental inputs to the standard model of auto speed cannot be investigated. Instead, an innovation in this study is to model observed road speeds, calculated from the activity diaries, as a function of built environment characteristics near home and/or work. Individual demand for auto travel on the network is presumptively an increasing function of speed, and observed speed is the reciprocal of the equilibrium price. If the demand for out-of-home activities is elastic, or competitively priced alternative modes are available, demand for non-work auto travel will be elastic—that is, an increasing function of network speed. So, traffic density D is hypothesized to be an increasing function of the number of potential network users D_{NL} with a negative second derivative, and speed S is a decreasing function of the number of potential network users:

$$S = a[1-(b[f(D_{NL})]/w)^c]^d .$$

For estimation purposes, it is assumed that the function $f(.)$ is linear in arguments; that the nonlinearity of the function S can be represented as a linear function of squared or logged independent variables; and that we observe the straight-line (as-the-crow-flies) speed of trips. Then speed can be represented as a linear function that can be estimated using ordinary least squares:

$$S = \boldsymbol{\alpha}\mathbf{D}_{\mathbf{NL}} + \boldsymbol{\beta}\mathbf{C},$$

where $\mathbf{D}_{\mathbf{NL}}$ is a vector of network load density measures (including squared terms), $\mathbf{C}$ is a vector of control variables including connectivity (as explained below), and $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ are vectors of coefficients to be estimated.

Four network load density measures are tested: population, employment, retail employment, and services employment per road mile, measured within given radii of the origin or destination of the trip. The employment-based measures are included separately under the presumption that retail and services employment attract larger numbers of trips and therefore may lead to more traffic controls and congestion.

The speed model takes two other infrastructure factors into account. First, design features of roads such as the number of lanes and the size of curb radii should affect speed. A variable representing total road miles is used to proxy for a *lower* design standard, because denser networks have narrower roads, contain a smaller percentage of freeways and high-capacity, multiple-lane roads, and fewer high-speed design features such as wide curb radii and shoulders.[6] Second, the more connected the network, the more direct the route between two points and the faster the speed *ceteris paribus*, because speed is measured here as reported travel time divided by straight-line distance between geo-coded street address points. Thus a variable representing the number of four-way intersections in the area is expected to have a positive sign *ceteris paribus*.[7]

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[6] This assertion is based on an inspection of the street segment map layer (vector shapefile) overlaid with the San Diego parcel map, which explicitly represents streets as shapes with measurable widths. Because a parcel map with explicitly represented street widths was not available for the San Francisco Bay Area I use center-mile street length in the analysis.

[7] The model cannot account for through-traffic, which may make up a substantial percentage of traffic in any area. However, one might expect that through-drivers, particularly using local roads, would avoid densely populated areas and seek routes through sparsely settled areas. If so, the existence of through traffic will tend to reduce rather than strengthen the estimated exogenous relationship of network load density with auto speed.

Four control measures are included. First, trip distance and distance squared are included as explanatory variables. Longer trips are expected to be faster because fixed time costs for short walks to the car and getting in and out of the car are spread out, and drivers have more opportunity to optimize their routes for speed (e.g., to use arterial roads and highways) and route directness. The squared term accounts for nonlinearity in the relationship with longer trips where the fixed time costs are spread out over a larger base. Second, to account for exogenous scheduling effects of the work week, a dummy variable is included indicating whether the travel day was a weekday. Third, to account for regional differences in network conditions, a dummy variable is included to indicate whether the trip took place in the San Diego metropolitan area.

The unit of analysis is one-way trips. For one-way trips with one terminal at work or school, network load density, network connectivity and network capacity are measured near the workplace or school location. For trips with a home terminal, the measures are from the residential location. For trips with both a work/school terminal and a home terminal, the average of both measures is used.

3.3.2 Analysis 2A: Non-work activities

A theoretically reasonable way to model travel choices is to treat the observed number of out-of-home activities (by mode of access) as an observed outcome of the individual's demand for out-of-home activity participation (by mode of access). When combined with information about how the person accesses the activity, this yields a model with dependent variables directly related to travel. The number of non-work activities by mode is specified as a function of the density measures under the assumption that a tractable representation of the demand process can be conventionally derived via a linear transformation of a household utility function subject to a time budget constraint.

Following an activity demand framework, activity frequency is modeled as a function of activity density and network load density, which influence the time price of accessing out-of-home activities; and built form density, affecting the utility of walking. Controls include the presence of children, sex, and age, reflecting tastes as well as non-budgetary constraints on travel. Finally, household income and income squared, the presence of children in the household, whether the traveler works outside the home, and whether it is a workday are variables representing money and time budget constraints,.

Non-work activity frequency by mode is estimated using a count regression function.[8] Count models such as Poisson and the negative binomial are consistent with treating activity frequency under conventional assumptions

[8] Although not a simultaneous modeling process, a set of count models is preferable to a mode choice model because it addresses both the share and the number of trips by each mode, and can be used to address mode substitution and induced travel simultaneously.

of utility maximization with a time budget constraint (Kockelman 2001). In the conditional exponential mean function of the Poisson, the functional form of the conditional distribution of the dependent variable given independent variables held constant is (Cameron and Trivedi 1998: 61):

$$f(y_i|\mathbf{x}_i) = \frac{e^{-\mu_i}\mu_i^{y_i}}{y_i!}, \quad y_i = 0, 1, 2$$

with exponential mean function

$$E[y_i|\mathbf{x}_i] = \mu_i = \exp(\mathbf{x}_i'\beta)$$

In the Poisson function the mean (μ_i) is equivalent to the variance. But, as with most count variables, the variance of non-work trips by different modes does not equal the mean in this dataset. Therefore the strict variance assumption is relaxed and the negative binomial model is used in place of the Poisson. The variance ω_i is parameterized as a quadratic function of the expected mean,

$$\omega_i = \mu_i + \alpha^2\mu_i \quad [= (1+\alpha^2)\exp(\mathbf{x}_i'\beta)\ ],$$

where **X** is a vector that includes density measures, built environment measures, and socioeconomic control variables and **β** is a vector of coefficients to be estimated.

The negative binomial model estimates larger variances than the Poisson model, leading to lower levels of statistical significance, but the estimated coefficients are the same. The pragmatic effect of using the negative binomial specification rather than the Poisson is to reduce the likelihood of finding statistically significant relationships.

3.3.3 Analysis 2B: Non-work auto mileage

Most respondents in the data set do not make a non-work trip via auto on the survey day. Because of the large number of zero observations, with the remainder of the sample following a continuous function highly peaked near zero, non-work auto mileage is readily treated as a left-censored normally-distributed dependent variable.

The number of miles traveled on personal commercial trips is an outcome of activity participation. Thus it is treated as a function of the same vector of variables **X** used in the activity frequency models, including density measures, other built environment measures, and socioeconomic control variables:

To account for the left-censoring, the Tobit regression is used:

$$VMT_i = \beta' x_i + \sigma \frac{\phi_i}{\Phi_i} + \varepsilon_i ,$$

where *VMT* is vehicle miles traveled, x is the vector of independent variables and β the vector of estimated coefficients on x; φ and Φ are the normal probability density function and cumulative density function respectively; σ is the estimated coefficient on their ratio; ε is the error; and i is an observation subscript (following Maddala 1983: 159, eq. 6.36). The ratio in the second term is typically estimated using a separate probit regression to get values of φ_i and Φ_i, in which the dependent variable is set equal to one if total personal commercial VMT is zero, and zero otherwise. The final model above can be estimated as an OLS regression in which σ is a coefficient. (The independent variables are the same for both the probit model and the OLS model.) Here, Stata's "tobit" command is used to estimate both equations using a maximum likelihood routine, asymptotically equivalent to ordinary least squares (Stata Corporation 1997: 138, 145-6).

4 Results

4.1 Analysis 1: Auto speed

As shown in Table 3, auto speed is significantly correlated with residential network load density (residents per road mile). A standard deviation increase in residential network load density, measured at the one-mile radius around home (221 residents per road mile), is associated with a reduction of 1.26 miles per hour in straight-line speed, a 13 percent reduction from the mean. The other network load density terms—retail network load density, service network load density, and all-worker network load density—are statistically insignificant although relationships are generally in the expected direction. This may be because the speed data are error-prone due to self-reporting and rounding; because the variables are more poorly measured; or because retail and services are highly correlated with wider streets nearby (e.g., good access to freeways and major arterials). This suggests the need in future research to calculate more precise measures of local transportation capacity, such as lane miles, in constructing the network load density measures.

None of the squared network load density terms, used to test whether exponentially greater congestion (lower speed) results from higher numbers of potential users nearby, is found to be significantly correlated with auto speed. This supports the theory that increasing network load density at low levels leads to the imposition of traffic controls, slowing speeds down somewhat, before congestion sets in at higher levels of network load density to slow things down even more – with a roughly linear relationship as the net result. The base model is the best-fitting model among those estimated as well as the easiest to interpret.[9]

4.2 Analysis 2A: Non-work activities

Tables 4 through 7 show models of non-work activity participation by mode of access (auto, transit, and walk/bike). Several models, each with a different set of density measures, are estimated for each dependent variable.

[9] It might be argued that distance to the central business district (CBD) is correlated with network load density and road congestion when controlling for other factors. Distance to the CBD has been hypothesized to be a proxy for transportation infrastructure provision and distance to major activity centers (Levinson and Kumar 1997). Nearest-CBD indicator variables, and interactions with distance, were included in the speed models. All variables were statistically insignificant and of small magnitude when network load density measures were included (results available from the author).

4.2.1 Non-work activities accessed by personal vehicle

When added singly to a regression on personal-vehicle-accessed activities, each of the density measures is significantly correlated with fewer non-work activities accessed by automobile (Table 4).[10] Activity density measured in the 1-to-3 mile ring is statistically significant, with a 1.1 percent reduction associated with each additional 1,000 retail employees in that spatial range (a 15 percent reduction per standard deviation). While one would expect greater activity density to result in more auto-accessed activities, the magnitude and statistical significance of this variable declines when other density measures are controlled.

[Table 4]

Residential network load density has a strong negative correlation with the frequency of automobile use for non-work activities (column 2). Each marginal increase of one thousand residents per road mile is correlated with a 63 percent reduction in the number of auto-accessed nonwork activities. This translates to a 20 percent reduction per standard deviation increase on this measure. The result is consistent with the expectation that by slowing down auto speeds, network load density decreases per capita nonwork travel by car.

Built form density at the 1/4-mile radius scale is strongly correlated with lower auto use (column 3): each additional 100 residents and employees per

[10] "Automobile" includes travel in all personally-operated vehicles, including trucks and motorcycles, whether or not the respondent is the driver.

developed acre is correlated with a reduction of 47 percent (a 32 percent reduction per standard deviation increase on this measure).

The most strongly related density measures of the three types measured are included in the last two models (columns 4 and 5). Only built form density retains statistical significance, while coefficients on all density measures decrease in magnitude. The final model, including an interaction between high activity density and low network load density, provides renewed evidence for the importance of activity and network load densities, although only when combined.[11] As hypothesized, this combination is associated with a higher frequency of auto-accessed non-work activities, when controlling for the combined density measures, as shown in the final column. All else equal, high activity density combined with low network load density is associated with a 50 percent greater frequency of auto-accessed non-work activities. Interestingly, the magnitude and statistical significance of activity density at the 1/4-mile radius increases when this interaction variable is included, because in the presence of the interaction variable, the activity density variable signals the effect of increases

[11] Five interactive dummy variables were tested: below-median residential network load density (1-mile radius) in combination with above-median activity density at three scales (1/4-mile radius, 1/4-to-1-mile ring, 1-to-3 mile ring); below-median network load density in combination with above-median built form density (1/4-mile radius); and above-median activity density (1/4-mile) in combination with above-median built form density (1/4-mile). In regressions not shown here all five were added to the model shown in column 4. The built form density interactions were not significantly related. Of the remaining interactions between activity density and network load density, only the first was statistically significant jointly with others or singly.

in activity density when network load density is high. This partly explains the previous result in column 1: activity density often signals high network load density, and in that case activity density may result in fewer, rather than more, auto-accessed nonwork activities.

4.2.2 Non-work activities accessed by public transit

Turning to transit-accessed activities, Table 5, column one provides an initial test of the hypothesis that nearby activity density increases the frequency of activities. The model shows one statistically significant effect, a surprising negative correlation with activity density in the 1/4-to-1/2-mile ring.

[Table 5]

Measures intended to represent the level of transit service are included in column 2. These are residential network load density (expected to slow buses down), along with dummy variables indicating the presence of light or heavy rail stations within a half-mile of home. Only heavy rail proximity is highly and significantly associated with non-work transit trips. Absent an explicit measure of *bus* access in this dataset, heavy rail proximity is a likely proxy for particularly good bus access within the Oakland and San Francisco areas (there is little heavy rail outside those areas). Most non-work transit trips are carried out via bus. Also included in all models is the straight-line distance in miles to the nearest central business district (CBD), a proxy for the fact that the bus network in the four regions and sub-regions tends to decline in coverage density and service frequency with increasing distance from the major employment and activity center.[12] CBD distance is highly significant in the model; each additional mile of distance from the central business district is associated with between 20 and 36 percent fewer transit trips for non-work purposes, across all models in Table 5. Note, however, that this result holds only for San José and San Diego, not for Oakland and San Francisco, as implied by the opposite-in-sign, roughly equal-in-magnitude coefficients on the distance variables specific to those latter areas.[13]

Measures of built form density are expected to be positively related to the frequency of non-work activities accessed by transit, following the hypothesis that the measure signals attractive walking environments between home and the transit stop. But as seen in column 3, built form density is not statistically significant. In the next model (column 4), each type of density measure is simultaneously controlled. The result is a highly significant negative correlation of activity density in the 1/4-to-1/2 mile ring along with a significant positive correlation with built form density in the same spatial range. The measured

[12] Distance to the CBD is also correlated with development density and possibly therefore with congestion, but as discussed previously, the CBD variables are statistically insignificant in the road speed model when network load density is included.

[13] Though not the focus here, the other CBD variables represent the marginal differences associated with the distance from different sub-area CBDs. The coefficients on the Oakland and San Francisco CBD distance value are positive and actually somewhat greater in magnitude than the negative effect implied by the value for the generic distance. Interpretation is slightly tricky; this result implies that in the San José and San Diego areas, transit-accessed activity frequency drops off substantially as a function of distance from the CBD while in the San Francisco and Oakland areas, there is no such dropoff.

coefficients for both variables increase in magnitude and statistical significance from the single equation models. Network load density remains statistically insignificant. The activity density result could be due to substitution between walking and transit use. Those who walk use transit much more and vice versa, as shown in the "reduced form" table showing final models for all modes simultaneously (Table 7). The built form density result is harder to explain because we would expect built form density to be influential on both walking and transit use, but as we will see, built form density does not have a statistically significant correlation with walking except in combination with other measures.

Finally, none of several interaction terms tested were found to significantly predict public transit usage, and thus the transit table does not show a model including interactions.

4.2.3 Non-work activities accessed by walk/bike

Accessing non-work activities by walking or bike would most likely be strongly influenced by the presence or absence of nearby activities and of qualitative characteristics of the built environment, which are represented by the activity density and built form density variables respectively. Density measures of other types and scales are also tested, primarily for their possible influences via other travel modes (Table 6).

[Table 6]

Activity density measures were not found to significantly influence the number of non-work activities by walking or biking (columns 2, 4, and 5). By contrast, network load density has a large and statistically significant correlation with the use of walking and biking to access non-work activities in all models in which it was entered (columns 2, 4 and 5). The corresponding standard-deviation-normed increase is a 51 percent increase per additional 220 residents per road mile. The network load density measure is included primarily to proxy for road slowing, as was shown to be at work in the speed model, but it might also indicate more crowding on sidewalks, or even a pedestrian orientation to whatever retail uses are present. When sidewalks can get crowded, some people will find walking more enjoyable and feel safer (Jacobs 1961). Like the activity density measure, built form density measures were not found to have a significant independent correlation (columns 3 and 4), but the presence of a sidewalk was positively correlated in one model (column 3).

In the model presented in column 5, being above the median on all three density types is highly significant, associated with a four-fold increase in walk/bike-accessed activities. Note that the combination of just built form density and network load density is associated with an 83 percent reduction when all three density types in combination are controlled. This means that being over the activity density threshold adds 83 percent to the threefold increase associated with high built form density and high network load density. The final model implies the importance of simultaneously high values on all kinds of density in walk/bike-access activity frequency.

4.2.4 Reduced form models

The "reduced form" models presented in Table 7 allow a more convenient and complete exploration of substitution effects among modes. More activity participation by transit might mean less activity participation by auto, and vice versa; and measures which influence one mode directly might have indirect effects on the other modes. Most studies have focused on only one mode category, typically the private vehicle.

In the "#1" models, the effects of built environment measures on activity participation by one mode of access can be inspected as to whether in turn they appear to influence activity participation by another mode of access, including the interactive variables from previous tables. In the "#2" models, activity frequencies by the other two modes are included as independent variables. Obviously there is a strong presumption of statistical bias here, because the number of activities accessed by other modes is endogenous. The point is to observe whether the density variable and interaction coefficients are sensitive to including activities by other modes. If so, this provides evidence that substitution effects are important. One would expect *a priori* that influences increasing the likelihood of auto trip making would tend to decrease the use of walking and transit, while walking and transit use might be complementary.

Looking at the "#1" models first, just one of the interactive dummy variables (cells highlighted in grey) has a statistically significant relationship, and it is in the opposite direction from what might have been expected. Low network load density combined with high activity density is associated with an 84 percent increase in walk/bike-accessed activities, not a reduction as expected. The "#2" models suggest that auto-access and transit-access out-of-home non-work activities are strong substitutes. This may be due to commute-chained nonwork trip making. Second, transit-access and walk-access activities are strong complements. This relationship may be primarily due to households with less than one car per adult. Finally, auto-access and walk-access activities are not strongly related.

4.3 Analysis 2B: Auto mileage

Table 8 shows two regressions of total auto mileage on activity density, other built environment controls and sociodemographic variables, and residential network load density.[14] Built environment measures from the reduced form models for the trip analysis are used in auto mileage Model 1 (see Table 8).

In Auto mileage Model 1, higher residential network load density is associated with lower mileage, with a fairly large magnitude relationship.

[14] Because of dependent variable truncation (described above) the auto mileage analysis results should be viewed as generally less reliable than the analysis of activity participation by mode. Also, the dependent variable is not an estimate of the actual distance driven, because the calculation is based on straight-line rather than network distance, and because return trips are not included.

Activity density is also strongly negatively associated with mileage. In combination with the activity frequency models, this implies that higher activity density reduces the average distance per auto trip, and that shorter distances to desirable destinations might also cause substitution from auto travel into transit (but recall from Table 7 that in the case of walk/bike, there is little evidence of substitution from auto trip making).

Auto mileage Model 2 was created in order to explore the non-intuitive positive correlation of heavy rail transit access with auto mileage. This model includes additional measures of the distance to the nearest central business district (to control for distance to major activities) and of built form density in the quarter mile around home (to proxy for parking availability). The dummy variable denoting that San Francisco is the nearest CBD, and the built form density measure at the quarter mile radius, are highly negatively correlated with auto mileage, and the statistical significance of other variables is reduced, particularly residential network load density.

One interpretation of this result is that the availability of parking—and hence both the frequency of auto use and the ownership of autos—is the most significant influence on auto mileage. If so, this finding again suggests the importance of the effects of the built environment on auto inconvenience—in this case, parking search time and/or monetary cost, rather than slower road speeds.

Another interpretation is that residential network load density may *increase* the distance of non-work auto trips at the same time that it decreases their frequency, leading the net effect on VMT to be about neutral in a statistical sense (though the sign remains in the expected direction and the magnitude is fairly large). This possibility can be illustrated with a table of time cost for trips to “local” and “regional” destinations for travel originating from two different neighborhoods, or in a place before and after a land use change (Table 9). In response, the individual’s preferred destination choice may also change depending on the relative characteristics of the local and regional destinations (e.g., differences in price, quality, or selection of goods). In this example, the unintended result of allowing congested roads (or reduced parking availability) in a new mixed-use subdivision could be longer trips, and even an increase in auto mileage, depending on the elasticity of demand for out-of-home activities.

The strong statistical significance of the CBD variables may be an artifact. Roads farther away from CBDs and other job centers were likely built at higher capacity. If the distance to the CBD serves as an inverse measure of average auto capacity, then refined network load density measures using lane miles rather than center-line miles might reduce the CBD variables to insignificance.

5 Discussion: Hypothesis Tests

Of the hypotheses about the effects of the three density types (see section 2.1), the first was that activity density is not highly independently correlated with travel when controlling for other density types. This is largely borne out by the analysis. Activity density does not have an independent statistically significant relationship with VMT or activity frequency by mode in the final models, although it does when interacted with the other variables. Hypothesis 2 is also supported: residential network load density has a fairly consistent relationship with auto speed, activity frequency and VMT, both singly and when interacted. Hypothesis 3 finds less support, although an interesting result emerges. Contrary to expectation, built form density is most strongly (negatively) related to auto-access activities, rather than having a direct correlation with walking. This may be due to a correlation of built form density with parking availability.

For the scale hypotheses (section 2.2), there is more ambiguity. In the case of activity density, measures taken at smaller radii are more highly correlated with walking frequency than with auto frequency, and vice versa. But, though it is difficult to distinguish direct from indirect effects, it seems clear that in some cases the expected relationships do not hold. One example is that residential network load density measured at the one-mile radius is strongly positively correlated with walk/bike-access activities. The reduced form activity frequency model (Table 7) suggests this result is not due to substitution from auto trip making, because there is little evidence that the number of auto trips is negatively correlated with the number of walk/bike trips, *ceteris paribus*. Instead the residential network load density measure may be a proxy for the scale of the potential pedestrian market for commercial activities, which is likely highly correlated with the availability of pedestrian-oriented retail and services establishments.

Finally, the interaction hypotheses (section 2.3) find significant support. The interactions among the density measures are often highly significant, with results that make intuitive sense. High activity density and low network load density in combination lead to more non-work auto trips, by bringing opportunities near to home at the same time that the roads are kept relatively uncongested. This result confirms a more explicit version of the hypothesis first articulated by Crane (1996) that bringing origins and destinations closer together might increase rather than decrease auto trip frequency. On the other hand, high network load density, activity density, and built form density working in combination have a striking positive correlation with the frequency of non-work activities. This conforms to expectation that the combinations of a high-quality walking environment, nearby activities, and congested roads may encourage people to walk. The interactive variable results imply that without all of types of density increasing simultaneously, there will be little effect on walking.

5.1 Limitations

This study takes a conventional approach to modeling travel decisions, treating travel outcomes as a function of socioeconomic characteristics and built environment measures, and attempting to account for simultaneity by including measures that affect travel by all of the modes. A more complete model might treat activity participation and scheduling as the basic determinant of travel patterns, account for the built environment characteristics of other fixed activity locations (such as workplaces, for those who work outside the home), and/or explicitly model residential location choice and auto ownership as endogenously determined. In that sense, this paper is primarily a descriptive exercise providing evidence to inform models more completely accounting for causal hypotheses.

6 Policy Implications

Much previous analysis has suggested that mixed uses, density and street grid patterns near rail stations causes people to use transit and to walk in greater numbers by making shorter trips possible and by making transit easier to use. These results suggest that the reason for that conclusion may be omitted variable bias: previous research has failed to include network load density and the interactions among network load density, activity density, and built form density. Merely providing attractive environments and uses accessible to walkers and transit users may not alter travel behavior significantly.

Particularly in newly developing areas, street and parking standards are geared to making the auto convenient. With minimum street width requirements and other capacity-increasing street design standards, it is possible to achieve relatively high levels of population density and activity density near transit stations without increasing network load density (for a relevant discussion of Los Angeles, see Manville and Shoup (2004)). A new transit-oriented development could make jobs or non-work activities accessible via rail or bus to more residences *without increasing the time price of auto use*. The analysis presented here suggests such a change may increase alternative mode use only slightly, if at all. But if road design standards are relaxed, if network load density also increases, and in turn road speeds decrease, auto mileage may decline, particularly if transit and walking options are available. And the lack of substitution between auto and walk non-work travel evidenced in the results of the reduced form models (Table 7) implies that policies solely to make things better for walkers may not reduce driving.

Deciding how much to relax such standards could begin with an attempt to quantify the option value of land in uses other than roads and parking. Subdivision and master developers are well-positioned to assess and estimate these costs, for private as well as local public land uses.

The analysis presented here suggests that relaxing road and parking standards would reduce auto use and, under the right circumstances, increase walking/biking and transit use. If resulting congestion and parking spillovers can be appropriately managed with reforms (Shoup 2005) such as bundled off-street priced parking, on-street parking permitting and pricing, and road pricing, the answer would seem to be yes.

Absent those interventions, the question arises whether it is welfare-increasing to deliberately allow congestion to get worse in order to reduce auto use. The potential costs include time spent in traffic; inconvenience for those who alter their plans to avoid congestion or who suppress their travel entirely; and any significant health-impacting concentration of air pollutants in newly congested areas. The potential benefits include the use of land for economically productive or otherwise beneficial uses other than roads and parking; reduced region-wide pollution; increased positive transit ridership externalities; increased positive pedestrian traffic externalities; and a reduction in those emissions that cause global warming and ocean acidification. This study only begins to inform these policy questions, because it does not address the costs of modifying development density in order to achieve these ostensibly desirable outcomes.

The results also have implications for those who seek to implement transportation-oriented land use policies in order to reduce auto use. The larger-scale built environment near where people live is very important in influencing travel choices, as evidenced by the road speed model results which are best-fit to a one-mile radius, and by the auto mileage model in which distance to the CBD plays a large role. Based on the strong correlation of auto mileage with distance to downtown, for example, a transit-oriented development program that developed suburban rail station areas more densely might result in more auto mileage (compared to a contiguous development policy focused on infill areas)—even though auto trip making might be reduced.

Network load density, activity density, built form density, and pedestrian/transit-oriented design are not always highly correlated with each other in new development, but for historical reasons *are* highly correlated across urban areas in cross-sectional analysis. Research failing to control for each may erroneously conclude that high-density developments will reduce auto use, when whether this will happen is clearly dependent on the particular details and context of development.

7 Appendix

The quality-quantity-price framework relating the built environment to travel choices (see section 2.1) can be represented using standard microeconomic expressions, with an individual utility function, a time budget constraint, and a money budget constraint. Departing from Lancaster (1966), let individual utility be a function of the qualities of activities. The bundle of qualities is represented by a vector **q** containing scalar indexes representing the amount of each quality derived from the activities chosen during a given time period. The utility function may contain interactions with demographic variables **z**:

$$U = f(\mathbf{q}; \mathbf{z}). \tag{1}$$

Qualities are the goods consumed by participating in activities. The activity participation bundle, **a**, consists of all in-home, out-of-home and travel activities (measured in time units). A unit of time consumed in a given activity gives a characteristic vector of qualities, as described by transformation matrix **A**. Multiplying **a** by **A** yields a vector of qualities,

$$\mathbf{q} = \mathbf{A}\mathbf{a}. \tag{2}$$

To incorporate the hypothesized influence of built environment characteristics on the qualitative experience of travel, let **A** be a function of built environment characteristics **x:**

$$\mathbf{A} = f(\mathbf{x}). \tag{3}$$

Two budget constraints are needed. The first is the time budget constraint,

$$T = \sum_{i=1}^{n} a_{hi} + \sum_{j=1}^{m} a_{oj} + \sum_{k=1}^{p} \frac{d_k(\mathbf{x})}{s_k(\mathbf{x})}. \tag{4}$$

The constraint distinguishes between different types of activity included within the vector **a,** because in-home activities (a_h's) do not require travel, while out-of-home activities (a_o's) do. The third term is the sum of travel time to access out-of-home activities, which is represented in a simplified fashion as the average distance to each out-of-home activity accessed by mode k (d_k) divided by the average speed of travel for travel by that mode (s_k) over p modes. In other words, $a_{tk}(\mathbf{x}) = d_k(\mathbf{x})/s_k(\mathbf{x})$. The average speed s and the average distance d are hypothesized to be functions of built environment characteristics $\mathbf{x}$.

One further budget constraint completes the model. Built environment characteristics may not significantly affect the per-unit-distance money price of travel. However, the built environment, and particularly development density, may also influence the money price of parking for the auto mode. Therefore, built environment characteristics $\mathbf{x}$ appears in the money budget constraint

$$wa_w + r \geq \sum_{i=1}^{n} a_{hi} p_{hi} + \sum_{j=1}^{m} a_{oj} p_{oj} + p_a(\mathbf{x}), \tag{5}$$

where w is the wage rate, a_w is the time spent in wage labor, r is non-wage income, the p_h's and p_o's are money prices per hour for in-home and out-of-home activities, and p_a is parking cost as a function of built environment characteristics.

The household or individual maximizes utility over activities (equation 1), given the qualities inherent in activities (equation 2) and the influence of built environment characteristics $\mathbf{x}$ on the qualities of travel by the different modes (equation 3), subject to time and money budget constraints via distance, speed and parking cost that are influenced by built environment characteristics $\mathbf{x}$ (equations 4 and 5). The built environment (BE) has income and substitution effects within this model, and these can be complex in interaction. But to put it simply, BE-induced increases in auto speed can be expected to increase auto travel and possibly other modes by relaxing the time budget; BE-induced increases in distance to activities can be expected to decrease travel by decreasing the time budget; and BE-induced increases in the quality of travel can be expected to increase walking and possibly other modes by increasing the utility of travel as an activity.

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10 Tables

Table 1: Speed Model Variables

Measure	Units	Mean	St Dev	Min.	Max.
Straight-line auto speed (dep var)	Miles per hour	10.33	6.92	1.01	44.39
Worker network load density	Workers per road mile	0.36	0.37	0.004	3.13
Residential network load density	Residents per road mile	0.40	0.18	0.06	1.13
Retail network load density	Retail employees per road mile	0.08	0.09	0	0.45
Service network load density	Service employees per road mile	0.13	0.15	0	1.35
Cumulative road length	Miles	60.7	14.4	13.7	99.1
Four-way intersections	NA	125	98	7	458
Straight-line trip distance	Miles	2.31	1.30	0.50	4.98
Weekday indicator	1=weekday, 0=weekend	0.81	0.39	0	1

Notes: N=722. Variables measured within a 1-mile radius of the trip origin, destination, or average.

Table 2: Travel Model Variables

Measure (Radius)	Units	Mean	St Dev	Min	Max
Auto-accessed activities	Count	1.02	1.44	0	10
Transit-accessed activities	Count	0.05	0.27	0	3
Walk/bike-accessed activities	Count	0.28	0.72	0	6
Vehicle distance traveled	Miles (one-way)	3.61	7.19	0	44.1
Activity density (1/4-mi radius)	Retail employees	695	1,197	0	8,975
Activity density (1/4-1/2 mi ring)	Retail employees	1,697	2,675	0	16,707
Activity density (1/2-1 mi ring)	Retail employees	3,302	4,022	0	36,787
Activity density (1/2-3 mi ring)	Retail employees	19,668	13,524	0	81,138
Activity density (1-3 mi ring)	Retail employees	16,369	11,559	0	75,172
Network load density (1-mi radius)	Residents per road mile	448	221	10	1,458
Built form density (1/4-mi radius)	Residents+workers/dev. ac.	48	60	2	778
Built form density (1/4-1/2 mi ring)	Residents+workers/dev. ac.	47	64	1	711
Sidewalk on both sides of street?	Indicator variable (1=yes)	0.86	0.35	0	1
In San Diego metro area	0=no, 1=yes	0.40	0.49	0	1
Station area stratum, Bay Area	0=no, 1=yes	0.35	0.48	0	1
Station area stratum, San Diego	0=no, 1=yes	0.24	0.42	0	1
Age	Mid-point of standard ranges	46.30	16.87	21	85
Female	0=male, 1=female	0.57	0.50	0	1
Children in household	0=no, 1=yes	0.22	0.41	0	1
Weekday	0=no, 1=yes	0.76	0.43	0	1
Worked two hours or more	0=no, 1=yes	0.41	0.49	0	1
Household size	Count	2.22	1.31	1	10
Household income	Thousands of dollars	5.68	3.79	0	11

Notes: N=1,000 except vehicle distance traveled, N=528.

Table 3: Auto Speed Models, Trips Between 0.5 and 5 Mi, One-Mi Radius Measures

	Base Model	Emps/Rd Squared	Pop/Rd Squared	Ret/Rd Squared	Srv/Rd Squared
Workers per rd mi (1,000s)	0.377 (0.17)	-0.761 (0.29)	0.381 (0.16)	-0.139 (0.06)	-0.099 (0.04)
Workers per rd mi squared		0.549 (0.70)			
Residents per rd mi (1,000s)	**-6.792 (3.34)****	**-6.356 (2.66)****	**-15.434 (2.40)***	**-6.161 (2.60)****	**-6.641 (2.75)****
Residents per rd mi squared			10.189 (1.56)		
Retail workers per rd mi (1,000s)	-2.892 (0.77)	-4.239 (0.85)	-4.641 (0.96)	0.516 (0.04)	-3.667 (0.73)
Retail workers per rd mi squared				-15.345 (0.50)	
Service workers per rd mi (1,000s)	-3.477 (0.67)	-3.858 (0.62)	-3.728 (0.63)	-1.844 (0.30)	-7.343 (0.99)
Service workers per rd mi squared					4.71 (1.08)
Cumulative road length (miles)	**-0.056** (2.21)*	**-0.069** (2.24)*	**-0.06** (2.01)*	**-0.066** (2.18)*	**-0.073** (2.35)*
Four-way intersections (100s)	0.639 (1.26)	0.77 (1.19)	0.683 (1.11)	0.612 (0.99)	0.908 (1.36)
Straight-line trip distance (miles)	**4.637 (5.75)****	**4.691 (5.75)****	**4.602 (5.64)****	**4.685 (5.74)****	**4.683 (5.74)****
Trip distance squared	**-0.45 (3.00)****	**-0.457 (3.01)****	**-0.442 (2.91)****	**-0.457 (3.01)****	**-0.454 (2.99)****
Weekday indicator	0.264 (0.45)	0.281 (0.47)	0.272 (0.46)	0.282 (0.47)	0.281 (0.47)
Constant	**8.425 (4.77)****	**10.054 (4.22)****	**11.135 (4.47)****	**9.475 (4.11)****	**10.341 (4.32)****
Observations	722	722	722	722	722
R-squared	0.23	0.24	0.24	0.24	0.24

Absolute value of t statistics in parentheses

Table 4: Auto-Accessed Non-Work Activities as a Function of Density Measures (Negative Binomial Regressions)

	-1- Activity Density	-2- Network Load Density	-3- Built Form Density	-4- Combined Density Measures	-5- Density Measures + One Interaction
Activity density, 1/4-mi radius	-11.2%			-8.2%	**-14.1%**
	[1.60]			[1.33]	**[2.18]****
Activity density, 1/4-1/2 mile ring	-3.3%				
	[0.85]				
Activity density, 1/2-1 mile ring	-1.6%				
	[0.70]				
Activity density, 1-3 mile ring	**-1.1%**			-0.7%	-0.7%
	[2.10]**			[1.23]	[1.37]
Network load density, 1-mi radius		**-62.8%**		-22.6%	-0.5%
		[3.65]***		[0.71]	[0.01]
Built form density, 1/4-mi radius			**-47.0%**	**-33.0%**	**-36.0%**
			[2.19]**	**[1.94]***	**[2.08]****
Built form density, 1/4-1/2 mile ring			-2.8%		
			[0.13]		
High activity density (0-1/4 mi) +					**49.2%**
low network load density (0-1 mi)					**[2.79]*****
In S.F. Bay Area selected station area	18.5%	**23.5%**	17.1%	16.0%	20.0%
	[1.34]	**[1.68]***	[1.25]	[1.16]	[1.43]
In San Diego selected station area	**65.7%**	**9.8%**	**36.6%**	**43.3%**	**36.5%**
	[3.13]***	**[0.62]**	**[2.09]****	**[2.16]****	**[1.86]***
Respondent age	**5.3%**	**5.4%**	**5.4%**	**5.3%**	**5.2%**
	[3.23]***	**[3.24]*****	**[3.26]*****	**[3.23]*****	**[3.19]*****
Age squared / 100	**-5.2%**	**-5.1%**	**-5.1%**	**-5.1%**	**-5.1%**
	[3.36]***	**[3.33]*****	**[3.36]*****	**[3.35]*****	**[3.33]*****
Weekday (dummy)	-13.2%	-14.2%	-12.6%	-12.5%	-12.1%
	[1.20]	[1.30]	[1.15]	[1.14]	[1.11]
Worked 2 hrs or more (dummy)	-10.5%	-10.9%	-11.2%	-11.1%	-12.6%
	[1.03]	[1.07]	[1.10]	[1.09]	[1.24]
Household size	**-11.1%**	-7.9%	**-10.1%**	**-10.6%**	**-9.7%**
	[2.29]**	[1.62]	**[2.10]****	**[2.21]****	**[2.01]****
Household income in thousands	10.7%	10.2%	8.9%	9.0%	7.4%
	[1.35]	[1.29]	[1.13]	[1.14]	[0.94]
Household income squared	-0.4%	-0.4%	-0.3%	-0.3%	-0.2%
	[0.74]	[0.81]	[0.57]	[0.60]	[0.42]
Observations	1,000	1,000	1,000	1,000	1,000
Pseudo R-squared	0.03	0.02	0.03	0.03	0.03

Z-statistics in brackets. Statistical significance: * = 10%; ** = 5%; *** = 1%.

Not shown, statistically insignificant: San Diego metro area (dummy); female respondent; children in household; female with children in household; missing income; missing age.

Table 5: Non-Work Activities Accessed by Transit as a Function of Built Environment Measures (Negative Binomial Regressions)

	-1- Activity Density	-2- NL Density + Transit Service	-3- Built Form Density	-4- Combined Density Measures
Activity density, 1/4-mi radius	23.3%			
	[1.49]			
Activity density, 1/4-1/2 mile ring	**-19.6%**			**-35.8%**
	[1.92]*			**[3.09]*****
Activity density, 1/2-to-3 mile ring	0.8%			
	[0.58]			
Network load density, 1-mi radius		-88.0%		-75.8%
		[1.61]		[1.14]
Transit service: Light rail area		-0.2%		-7.3%
		[0.00]		[0.10]
Transit service: Heavy rail area		**464.6%**		**492.2%**
		[2.59]***		**[2.64]*****
Built form density, 1/4-mi radius			-34.5%	
			[0.88]	
Built form density, 1/4-1/2 mile ring			60.2%	**105.2%**
			[1.24]	**[2.48]****
Distance to major city center	**-25.4%**	**-20.8%**	**-17.3%**	**-36.1%**
	[2.47]**	**[3.54]*****	**[2.69]*****	**[4.30]*****
Dist. to CBD, Oak. area	**26.8%**	12.5%	14.6%	**38.7%**
	[1.76]*	[1.15]	[1.45]	**[2.65]*****
Dist. to CBD, S.F. area	**43.0%**	**39.0%**	**34.3%**	**40.2%**
	[2.05]**	**[1.79]***	**[1.79]***	**[1.82]***
In San Diego metro area	325.4%	203.3%	178.1%	**817.1%**
	[1.60]	[1.25]	[1.19]	**[2.48]****
Weekday (dummy)	127.5%	122.1%	139.4%	127.2%
	[1.59]	[1.53]	[1.66]*	[1.59]
Worked 2 hrs or more (dummy)	-29.9%	-32.3%	-32.3%	-38.6%
	[0.89]	[0.97]	[0.96]	[1.21]
Household size	13.6%	15.8%	11.9%	15.7%
	[0.79]	[0.91]	[0.67]	[0.91]
Household income in thousands	-6.2%	-12.6%	-8.8%	-8.6%
	[0.29]	[0.59]	[0.40]	[0.41]
Household income squared	-0.8%	-0.4%	-0.7%	-0.7%
	[0.42]	[0.19]	[0.37]	[0.36]
Refused to state HH income	-73.9%	**-80.5%**	**-79.3%**	-75.0%
	[1.47]	**[1.79]***	**[1.71]***	[1.54]
Observations	1,000	1,000	1,000	1,000
Pseudo R-squared	0.16	0.17	0.15	0.19

Z-statistics in brackets. Statistical significance: * = 10%; ** = 5%; *** = 1%.

Not shown, statistically insignificant: Sidewalk on both sides of street (dummy); distance to CBD, SJ area; Bay Area and San Diego station area strata dummies; age, age-squared, missing age; female respondent; children in household; female with children in household.

Table 6: Walk/Bike-Accessed Non-Work Activities as a Function of Built Environment Measures (Negative Binomial Regressions)

	-1- Activity Density	-2- Network Load Density	-3- Built Form Density	-4- Combined Density Measures	-5- Density Measures + Interacts.
Activity density, 1/4-mi radius	4.3% [0.50]			11.0% [1.16]	8.6% [1.17]
Activity density, 1/4-1/2 mile ring	7.9% [1.37]				
Activity density, 1/2-1 mile ring	-2.6% [0.98]				
Activity density, 1-3 mile ring	-0.4% [0.30]				
Network load density, 1-mi radius		**555.3% [2.25]****		**501.3% [2.09]****	**647.6% [2.16]****
Built form density, 1/4-mi radius			-13.8% [0.54]	0.5% [0.02]	
Built form density, 1/4-1/2 mile ring			45.1% [1.44]		
Sidewalk			**71.4% [1.77]***	61.2% [1.56]	
High network load density (0-1 mi) + high built form density (0-1/4 mi)					**-82.6% [3.40]*****
High for all density types					**425.9% [3.56]*****
Distance to major city center	**-7.3% [2.25]****	**-10.2% [3.94]*****	**-7.9% [2.82]*****	**-7.5% [2.64]*****	**-8.9% [3.08]*****
Dist. to CBD, S.J. area	8.1% [1.18]	**12.6% [1.89]***	10.1% [1.51]	9.8% [1.47]	**11.2% [1.73]***
In S.F. Bay Area selected station area	**86.6% [2.20]****	58.7% [1.61]	**87.4% [2.26]****	51.5% [1.44]	48.0% [1.34]
In San Diego selected station area	49.0% [1.18]	**133.1% [2.42]****	67.8% [1.60]	**111.1% [2.06]****	**105.1% [2.03]****
Worked 2 hrs or more (dummy)	**-46.8% [3.24]*****	**-47.1% [3.29]*****	**-47.5% [3.31]*****	**-48.1% [3.35]*****	**-47.5% [3.32]*****
Household size	-13.4% [1.42]	-14.6% [1.57]	-12.9% [1.36]	-13.0% [1.36]	-12.1% [1.26]
Household income in thousands	**-18.7% [1.81]***	**-18.7% [1.82]***	**-19.0% [1.84]***	-17.1% [1.62]	-15.7% [1.50]
Household income squared	**1.7% [1.91]***	**1.8% [2.00]****	**1.7% [1.92]***	**1.7% [1.83]***	1.5% [1.63]
Observations	1,000	1,000	1,000	1,000	1,000
Pseudo R-squared	0.11	0.11	0.11	0.11	0.12

Z-statistics in brackets. Statistical significance: * = 10%; ** = 5%; *** = 1%.

Statistically insignificant, suppressed: Distance to CBD indicators; San Diego metro area; age and age-squared; female; children in household; female with children; weekday; missing income; missing age.

Table 7: Reduced Form Non-Work Activity Models, by Mode

	-1- Auto #1	-2- Auto #2	-3- Transit #1	-4- Transit #2	-5- Walk/Bike #1	-6- Walk/Bike #2
Nonwork activities via walk/bike		-2.0% [0.29]		**37.9% [2.48]****		
Nonwork activities via transit		**-55.3% [2.84]*****				**77.9% [2.37]****
Nonwork activities via auto				**-37.4% [2.25]****		5.3% [0.91]
Activity density, 1/4-mi radius	**-15.0% [2.31]****	**-13.3% [2.03]****			4.0% [0.55]	7.4% [0.98]
Activity density, 1-3 mile ring	-0.8% [1.56]	-0.7% [1.35]				
Network load density, 1-mi radius	17.8% [0.39]	-0.7% [0.02]	-87.9% [1.36]	-84.2% [1.44]	**694.4% [2.21]****	**591.9% [2.05]****
Built form density, 1/4-mi radius	**-34.8% [2.01]****	**-33.6% [1.93]***				
High activity density (0-1/4 mi) + low network load density (0-1 mi)	**47.8% [2.65]*****	**48.3% [2.75]*****	71.4% [0.85]		**83.8% [2.14]****	
High network load density (1-mi) + built form density (1/4-mi)	-20.1% [1.30]		24.9% [0.30]		**-79.4% [3.01]*****	**-81.3% [3.19]*****
High network load (1-mi), activity (1/4-mi) & built form (1/4-mi) density	18.8% [0.94]		85.9% [1.06]		**408.4% [3.46]*****	**387.1% [3.35]*****
Activity density, 1/4-1/2 mile ring			**-37.7% [3.08]*****	**-39.0% [3.29]*****		
Built form density, 1/4-1/2 mile ring			**106.3% [2.47]****	**121.3% [2.68]*****		
Transit service: Heavy rail area			**479.9% [2.81]*****	**394.1% [2.58]*****	13.5% [0.40]	10.7% [0.32]
Observations	1,000	1,000	1,000	1,000	1,000	1,000
Pseudo R-squared	0.03	0.03	0.20	0.23	0.13	0.13

Z-statistics in brackets. Statistical significance: * = 10%; ** = 5%; *** = 1%.
Included in models, suppressed: Sociodemographic variables; CBD indicator and distance variables (consistent with final models in mode-specific tables).

Table 8: Auto Mileage as a Function of Built Environment Characteristics

	Model 1	Model 2
Activity density (1/4-mile radius) Retail workers (1,000s)	**-2.321** **[2.94]*** **	-1.19 [1.08]
Activity density (1-mile radius) Retail workers (1,000s)	**-0.137** **[1.68]***	0.02 [0.16]
Network load density (1-mile radius) Residents (1,000s) per road mile	**-18.942** **[1.71]***	-13.066 [0.95]
Transit service: light rail area Light rail stop within 1/2 mile (SD, SJ)	2.993 [1.17]	1.466 [0.73]
Transit service: heavy rail area BART, Caltrain within 1/2 mile	**4.094** **[1.69]***	2.88 [1.37]
Pedestrian connectivity (1/4-mile radius) Number of 4-way intersections	-0.042 [0.44]	0.077 [0.71]
Built form density (1/4-mile radius) Workers + residents (1,000s) per developed acre		**-8.374** **[1.77]***
Distance to nearest central business district		-0.097 [0.61]
San Francisco nearest CBD		**-25.809** **[2.09]****
Distance to San Francisco CBD (Bay Area only)		4.697 [1.64]
Respondent age	**0.569** **[2.64]*****	**0.557** **[2.58]****
Age squared	**-0.006** **[2.84]*****	**-0.006** **[2.78]*****
Weekday (dummy)	**-2.883** **[1.70]***	-2.667 [1.56]
Household size	**-1.385** **[1.96]***	**-1.355** **[1.92]***
Constant	-9.522 [1.27]	-10.713 [1.21]
Observations	527	527

Note: The following variables are included in the estimation but are not displayed above and are statistically insignificant: Household income and income squared; female respondent; children in household; female with children in household; worked for pay on survey day; survey region (Bay Area or San Diego), station area (inside or outside a selected transit-oriented development area), missing household income, missing age, distance to San Jose and Oakland CBDs.

Absolute value of t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Example Trip Cost (Minutes) Before and After Decrease in Local Parking Availability

Mode/distance	Before	After
Auto/local	**5**	**15**
Auto/regional	15	**15**
Walk/local	15	**15**
Walk/regional	60	60
Transit/local	20	20
Transit/regional	35	35