Does Neighborhood Design Influence Travel?:
Behavioral Analysis of Travel Diary and GIS Data

Randall Crane
Departments of Urban Planning and Economics
Institute of Transportation Studies
University of California
Irvine, CA 92697-7075

Richard Crepeau
The Institute of Public Policy
George Mason University
Fairfax, VA 22030-4444

Working Paper
January 1998

UCTC No. 374

The University of California Transportation Center
University of California at Berkeley
Does Neighborhood Design Influence Travel?:  
A Behavioral Analysis of Travel Diary and GIS Data

Randall Crane  
Departments of Urban Planning and Economics
Institute for Transportation Studies
University of California, Irvine, CA 92697-7075  
(714) 824-7334/rdcrane@uci.edu

and

Richard Crepeau  
The Institute of Public Policy
George Mason University
Fairfax, VA 22030-4444  
(703) 993-2261/r.crepeau@worldnet.att.net

Revised: January 1998

ABSTRACT
Can urban design improve the environment? If communities could be designed to reduce automobile use, then yes. But can urban design influence travel? Surprisingly perhaps, the effects of any specific neighborhood feature on travel behavior at the margin are all but unknown. The policy significance of this issue is reflected in the swelling popularity of the “new urbanism” and other planning strategies employing land use tools to mitigate the environmental impacts of metropolitan development. In addition to asserting that development patterns and densities affect how far, how often, and by what means people travel, urban designers frequently argue that the legibility and shape of the local street pattern play a key role. “Connected” residential blocks are thus associated with less driving by comparison with the circuitous routes of the modern suburban cul-de-sac — chiefly by reducing trip lengths and facilitating pedestrian and transit access.

Remarkably, there is little empirical and theoretical support for these claims. This paper provides the first direct tests of these hypotheses within a consistent behavioral framework. An analysis of household travel diary and GIS data for San Diego finds little role for land use in explaining travel behavior, and no evidence that the street network pattern affects either short or long non-work travel decisions. While results may vary in other areas, the empirical argument for using land use as an element of regional air quality or other environmental plans remains to be demonstrated.

* We are most grateful to two anonymous referees, Marlon Boarnet, Charles Lave, Brian Taylor, and participants at the 1995 meetings of the Western Economics Association in San Diego, the 1996 ACSP/AESOP meetings in Toronto, and seminars at the University of Washington, Portland State University, USC, and UC Berkeley for helpful comments on earlier versions. Nick Compin and Dru van Hengel provided excellent research assistance. The U.S. and California Departments of Transportation and the University of California Transportation Center generously supported this research.
1. Introduction

Much of the history of urban design has concerned mundane issues of family travel. These travel patterns vary with the cultures, technologies, and characteristics of places and their people, and designers have had varying success imposing either order or style on each. In some cases the distribution of households, their work and school sites, and their shopping and recreational activities have been planned to follow routes that, in principle, minimize the social costs of pollution, traffic, and land use conflicts and maximize the social benefits of interaction and community (e.g., Southworth and Owens, 1993; Southworth and Ben-Joseph, 1995). In other instances, no clear role is played by design per se, or even perhaps planning, and the paths linking trip origins to trip destinations evolved ad hoc from the cumulative ebbs and flows of the marketplace.

While most urban patterns fall somewhere between these two extremes, loud and compelling calls to reduce automobile travel continue, thus minimizing its negative environmental impacts. Many of these arguments have been most visibly associated with the popular urban design schools of “neotraditional planning” or the “new urbanism” (Katz, 1994; Fulton, 1996; ITE, 1997) while others are advanced as part of regional air quality improvement strategies (Frank, 1997). Some schemes are grand, such as severely restricting car use within certain metropolitan areas or increasing driving costs several fold, and some focus on reducing the driving distance between locations while increasing the viability of alternative modes of travel (e.g., Kelbaugh, 1989; Beimborn, et al., 1991; Duany and Plater-Zyberk, 1991, 1992; Bookout, 1992; Calthorpe, 1993). In most such cases a basic assumption is that these elements will cause people to drive less than they do now.

While the debate continues regarding the validity of these arguments, many cities and metropolitan areas have implemented land use-based transportation policies either as guiding principles or goals in long-range transportation plans (e.g., 1000 Friends of Oregon 1993, County of Ventura 1997). These policies explicitly state as outcomes, reduced congestion, reduced sprawl and improved air quality.
Is this warranted? One difficulty with the literature on these questions is that the various elements of the new designs have rarely been studied in detail. While several studies have looked at whether “pedestrian friendly” neighborhood characteristics actually lead to more walking trips, for example, they have not evaluated the contribution of each characteristic individually. In particular, though often identified as a central contributing factor behind increased driving, the role of the neighborhood street layout on local travel has rarely been studied explicitly. Other issues in the literature concern the empirical methodologies used to date. We argue below that they are not up to the task of addressing these questions credibly.

What does it matter? If urban design strategies aimed at reducing auto use might work, why not try? Crane (1996a,b) has argued that such plans could well backfire, leading to more driving. In particular, these communities will tend to generate more car trips rather than fewer in many circumstances that designers have thus far failed to account for. Whether this results in more miles of travel by car depends in part on how sensitive the demand for each mode is to changes in the time required for each trip, and how well one mode substitutes for another. That is more likely if auto use is highly sensitive to changes in the time required for each trip, which in turn depends on the many characteristics of the circumstance, the driver, and the trip purpose. Owing to their countervailing effects on the costs and benefits of car travel, such land use policies as mixing land uses or intensifying development are similarly unclear in theory. But aside from this conceptual ambiguity, the more general point is how land use influences individual travel at the margin is not sufficiently well understood to be the basis for environmental policy.

If the theoretical basis for stating that neotraditional subdivision plans will reduce car travel is questionable, the next question is what happens in practice. We argue below that past empirical analyses of this important issue — how urban design affects travel — provide little if any support for the frequent contention that properly designed communities will generate less auto travel as a
matter of course. Our work substantially improves the methodology for examining these issues in
two critical respects. First we estimate a carefully specified behavioral model. Nearly all past
approaches are ad hoc constructions based on the data at hand while ours employs a standard
economic model of travel demand. In addition we make use of highly disaggregate data at the
individual and household level with respect to both travel decisions and land use.

As background, the next section organizes and reviews the pertinent literature. Section 3
summarizes the behavioral framework as a basis for the empirical strategy. Finally, Section 4
examines household level travel diary and GIS data for San Diego for evidence on these issues, by
way of both simple tests of differences of mean trip generation rates, mode choice and vehicle miles
traveled (VMT) in different neighborhood networks as well as regression analyses of these
decisions. We find little role for land use in explaining travel behavior in our sample, and in
particular no evidence that the street network reduces either short or long non-work auto travel.
While results may vary in other areas, our view is that the empirical argument for using land use as
an element of regional air quality or other environmental strategies remains to be demonstrated.

2. The Literature

A lively and diverse literature continues to investigate the potential for causal links between
urban design and travel behavior. This work has traditionally concerned the impacts of
transportation infrastructure on land use and urban form but a number of recent studies, encouraged
in part by policy initiatives such as ISTEA (Intermodal Surface Transportation Efficiency Act of
1991), also consider the potential for using land use planning to influence travel demand. Among
these, transit-oriented development research and “new urbanism” policies have been particularly
visible (Cervero and Seskin, 1995; Fulton, 1996). Their goals are many but feature reducing
“sprawl”, reducing traffic congestion, improving rail transit’s viability, and increasing the pedestrian
orientation of neighborhoods. These proposals currently hold great sway in urban design and environmental policy debates and, somewhat more concretely, they appear to have influenced the planning of several major cities (e.g., Bernick and Cervero, 1996; Calthorpe, 1993; Duany and Plater-Zyberk, 1991).

Yet there remains considerable debate within academia regarding the merit, feasibility and prospects of the transportation planning components of these designs (e.g., Giuliano, 1991; Wachs, 1993; Ewing, 1997; Gordon and Richardson, 1997). The fact remains, for example, that very few completed developments explicitly subscribe to the new principles for transportation policy and those that do are relatively young. Hence those studies examining these issues have avoided a direct examination of neotraditional or new urbanist design. (An exception, with a quite different focus than ours, is Southworth, 1997). In the case of simulation studies, the proposed designs are hypothesized, or in the case of most descriptive and analytical studies a number of proxy communities are used that shared various features thought to reduce car use.

In many cases this body of work raises more questions than it answers. Those studies measuring how trip frequency and VMT vary by local street patterns have usually found that auto use is either higher or no different than in comparable settings with a less connected street network. Most other work has assumed trip frequencies fall or do not change, in others the data are insufficiently disaggregated to control for the most important variables. Perhaps as importantly, a straightforward framework for sorting out the independent effects of each component of neighborhood design on travel behavior is lacking in virtually each case. Much past research has lumped several design and travel characteristics together, making conclusions about the travel properties of individual street and neighborhood design features impossible to isolate. The clearest pitfall is the failure to separate out the effects of the circulation pattern, which in principle influences access for both cars and pedestrians, from the effect of street width and street-scape
features explicitly intended to slow cars and reduce traffic. Several pivotal aspects of the literature’s treatment of several of critical empirical issues are discussed point-by-point below.¹

**Fixed Trip Frequencies**

Simulation studies such as Kulash, Anglin and Marks (1990), and McNally and Ryan (1993) have found that a connected or grid street design reduces vehicle miles traveled (VMT) as well as slower average travel speeds. These findings are used to support many of Calthorpe's (1993) conclusions about the transportation benefits of neotraditional design. The conclusion regarding the transportation benefits of neotraditional design supports the intuitive finding that connected street patterns reduces the distance of trips. However, one assumption made for these simulations is that trip frequencies are fixed. This work thus mainly demonstrates that if you move trip origins and destinations closer together, by opening up the circulation system for example, then car trips will be shorter by construction. Ignoring the consequence of street design on trip generation is to neglect what may be a more important transportation consequence of the new designs, and certainly ignores the behavioral consequences implicit in the reduction of trip lengths (see, e.g., Crane, 1996a,b).

**Disaggregating Neighborhood Effects**

Many studies attempt to measure the effects of neighborhood design on travel behavior. All of these develop an index of neighborhood qualities with terms such as Standard Suburban or Traditional (Gordon and Peers, 1992), Transit Accessibility, Pedestrian Accessibility and Neighborhood Shopping (Holtzclaw, 1994). In other studies, the neighborhood is somewhere on a continuum defined by design factors (Handy, 1996a, b; 1,000 Friends 1993).

¹ Other critical surveys of this literature and many of these issues can be found in Berman (1996), Boarnet and Sarmiento (1996), Cervero and Seskin (1995), Crane (1996a,b) and Handy (1996b).
What these studies lack is the ability to disaggregate the individual neighborhood characteristics' contributions to travel behavior. Gordon and Peers (1992) compared travel behavior between two neighborhood types. The Standard Suburban neighborhood type generated average trip rates 60% greater than Traditional neighborhoods and about 30% higher for home-based non-work trips. The standard suburban neighborhoods possessed a hierarchy of roads and highly segregated land uses, while traditional neighborhoods had grid streets and mixed land uses.

Handy (1992, 1996a) measured the effect of several categories of urban form on travel behavior, attempting to isolate the contributions of neighborhood and household characteristics. Her results suggest that the effects of neighborhood design are greater than the effects of household characteristics when comparing time, frequency and variety of trip destinations among the traditional and suburban neighborhoods. In this instance, neighborhoods are categorized and indexed by accessibility measures such as blocks per square mile, cul-de-sacs per road mile, commercial establishments per 10,000 population and accessibility to retail centers.

Holtzclaw (1994) found that neighborhood characteristics such as transit accessibility (bus and rail seats per hour weighted by the share of population within a quarter-mile of the transit stop) reduces both the number of cars per household and the VMT per household by almost 8%. The measure of pedestrian accessibility (which includes street patterns, topography and traffic) had no significant effect on household auto ownership or VMT. In Portland, Oregon, 1,000 Friends (1993) used a measure of pedestrian access to estimate the number of automobile trips. Here, pedestrian access was defined as a mixture of the ease of street crossings, sidewalk continuity, topography and whether a neighborhood street network was primarily cul-de-sac or more open. The authors found that increases in the pedestrian access index (indicating greater accessibility) decreased daily household VMT and daily car trips.
While these studies are able to suggest that general neighborhood designs do influence travel behavior, they are unable to attribute changes in travel behavior to any specific neighborhood design element. As an example, none of these studies were able to come to any conclusion about the transportation effects of neighborhood street design independent of any other design feature.

**Neighborhood Type**

Cervero and Gorham (1995) analyzed sets of paired communities in the San Francisco Bay Area and the Los Angeles-Orange County region. The pair-wise comparison tested for differences in commute behavior between automobile oriented communities and transit oriented communities. They hypothesized that transit oriented neighborhoods generate more pedestrian and transit trips. These neighborhoods were identified using street maps, transit service information and census data describing median household income. The travel data came from census data describing the journey to work, summarized by census tract. The authors suggest that street layouts do influence commuting behavior - transit neighborhoods averaged higher walking and bicycling modal shares and generation rates than did their automobile counterparts. However, this finding holds only for the Bay Area neighborhoods. In the Los Angeles-Orange County comparisons, the differences in the proportion of transit or pedestrian trips between the transit and automobile oriented neighborhoods were negligible. They suggest the sprawling nature of the region explain the weaker results for the Los Angeles-Orange County comparisons. In some ways, the potentially dominant role of the surrounding regional circulation pattern is a difficult hurdle for proponents of neotraditional design.

The weak results may have been due to the aggregated nature of the travel data. By comparing summary statistics among neighborhood census tracts, much information is lost. Not only variation in travel times within the tracts, but in assumptions made for socioeconomic data. If one is comparing the number of work trips, the number of workers (either in total or per household) is
essential information. However if comparisons are made only with income, it is unknown whether a high average income is the result of many or few workers (and therefore, generating many or fewer work trips regardless of transit or automobile influences). One can also question the focus of the commute when attempting to empirically test the influence of the street network. It is the non-work trip that generates a majority of the local area travel.

Frank (1994) proposed to test the relationship between urban form and travel behavior at the census tract level. In this study of the Puget Sound region of Washington State, Frank utilized data from a number of data sets that detail land use, travel behavior, jobs-housing balance and other relevant factors. While he states that street network patterns are among those variables that relate to urban form, the measure is not utilized throughout this extensive analysis. The finding most relevant to our study is that trip generation increased with levels of density and land use mix. However, these findings come not as a result of regression analysis, rather they result from simple correlation analysis. While Frank suggests that increasing density and land use mix is associated with increased work trip frequency, a significant relationship between density or land use mix and trip frequency could not be reported for shopping trip purposes.

Kitamura, et al. (1997) examines the influence of land use characteristics on travel behavior in five neighborhoods in the San Francisco Bay Area. These neighborhoods are defined as zones from a Metropolitan Transportation Commission land use data base. An innovation that is introduced in this analysis is the effect that attitudes have on travel behavior. The rationale for this analysis is to determine the relative contribution that residential living attitudes have on travel behavior beyond land use or neighborhood characteristics. The implications of this analysis focus on the suggested direction of transportation related policies -- should they take the form of land use decisions, or take into consideration the attitudes of commuters and travelers?
When considering only land use and socioeconomic characteristics, the authors regressed socioeconomic and neighborhood characteristics against the frequency and proportion of trips by mode. There is nothing surprising in the results -- parking availability was negatively associated with total person trips and positively associated with the proportion of automobile trips. High residential density was positively related to the proportion of non-motorized trips. Similarly, having a backyard and the distance to the nearest rail station were negatively correlated with the number and fraction of transit trips. What is unclear in the paper is the type of trips that are recorded in the trip diary. One might come to different conclusions if the trip purposes were disaggregated by type. It is assumed that commute characteristics are similar to non-work trip characteristics. They suggest that the explanatory power of the attitudinal factors was higher than neighborhood characteristics.

These studies, and others, depend on a definition of neighborhood that either is dependent on census geography (Cervero and Gorham, 1995; Frank, 1994; Holtzclaw, 1994; Kitamura et al, 1994; Kockelman, 1996) or on the delineation of a neighborhood (Handy 1996a). The danger of depending on census geography is that many of the household, travel and demographic characteristics are summary data and don't necessarily relate to the households in question that reside in that tract. On the other hand, dependence on the geography of the neighborhood relies on the assumption that all households are influence by that neighborhood and no others (i.e., households on the periphery of the neighborhood). These hurdles can be overcome through the use of a Geographic Information System (GIS). In the research we present, a buffer was drawn around each household in the survey and neighborhood characteristics such as street design within this buffer were observed.² The next section describes our approach in more detail.

² Boarnet and Sarmiento (1998) follow a strategy similar to ours in some respects, though with different data.
3. Behavioral Tests of Neighborhood Travel Determinants

The data and behavioral methodology in our study address most of these issues. The travel data are the 1986 Travel Behavior Surveys developed jointly by the San Diego Association of Governments and the California Department of Transportation (SANDAG, 1986b). The sample was obtained using a random telephone number "plus one" method which is said to eliminate biases against households that have unlisted numbers and households that have recently moved. Participants answered the socioeconomic questions over the telephone. Subsequently, the travel diary was sent to their home address and the information was collected for their travel characteristics on the designated travel day for that household. In total 2,754 households participated yielding data for 7,469 persons and 32,648 trips.

For this analysis, the data are restricted to those households where a successful address match was obtained based on the household's phone number (Drummond, 1995 discusses this procedure). In addition, this paper considers only non-work trips.\(^3\) The resulting sample yielded 4,199 home-based non-work trips, summarized in Table 1 and illustrated by location in the map of San Diego County in Figure 1. Note that by far the two most common mode choices were automobile and walking, with the latter at about 10 percent. Only about 3 percent of non-work trips were by transit in this sample.

\[\text{Table 1 is on page 24.}\]

\[\text{Figure 1 is on page 29.}\]

---

\(^3\) Though commuting travel cannot be ignored, the decision of where to live vis-a-vis where to work is both more constrained and more complex than for nonwork travel — involving labor and real estate market conditions among others (e.g., Crane, 1996c). It may also be relatively inflexible to changes in the local network. Still, this has been investigated by Cervero and Gorham (1995), Cervero (1995, 1996a,b) among others with some success.
Address matching of the travel survey records was needed to link these households and trips with U.S. Census TIGER files and geographic land use data from another San Diego Association of Governments 1986 report (SANDAG, 1986a, 1986c). The latter summarizes land uses by census tract in San Diego County. These data were obtained by aerial photography and site visits and thus represent actual land use rather than functional representations based strictly on political or zoning decisions. Though data are available on land uses at trip destinations as well as origins, our study currently restricts its attention to land use variables characterizing the home tract only. The variables describing the street network of the neighborhood are based on a visual inspection of the network within 1/2 mile of the household, using GIS software. The network was then judged to be either a "connected street" network, a "cul-de-sac" network, or a mixture of the two. An example of an observation in a “connected” neighborhood is given in Figure 2, while the distribution of the sample trips by street pattern is summarized in Table 2. The great majority of trips were thus by car, and most originated in cul-de-sac neighborhoods, though some walking trips and many connected areas are also represented.

[Figure 2 is on page 30.]

[Table 2 is on page 24.]

With respect to non-work travel, several decision margins are relevant to the question at hand. For example, there are the decisions of whether to take a trip, by what means to travel, and how far to go. Our first look at the data involves simple tests of differences in the mean responses to these questions by type of neighborhood, i.e., grids versus cul-de-sacs. Table 3 tests for significant differences in mean car trip length and Table 4 tests for differences in mean car trip speed.

---

4 Consider a hypothetical situation: A particular parcel of land may be zoned commercial but is vacant. The land use data here reflect the vacant status of the land, while the zoning information cannot capture this information. This is an important distinction to make when dealing with issues of transportation and urban form.
Both differences are significant, with trips starting in cul-de-sacs being less distant and also having a higher rather than lower average speed. This may reflect their more suburban location. Table 5 tests for differences in the mean number of car trips per household per day. It does not reveal a significant difference. The same was true for a comparison of the mean number of walking trips, not reported here. Indeed, the sample mean number of trips by car is higher and walking trips lower in cul-de-sac neighborhoods than in grids.

A simple comparison of means is incomplete in several respects, however. It has no behavioral content, as such, and it does not control for other factors behind these results other than the street network configuration at the trip origin. Indeed, the literature on the transportation impacts of these designs has yet to employ a formal conceptual framework when investigating these issues, making both supportive and contrary empirical results difficult to interpret. In particular, an analysis of trip frequency and mode choice requires a discussion of the demand for trips, but this is often lacking in land use studies at even a superficial level. That approach would permit one to explore the behavioral question, for example, of how a change in trip distance influences the individual desire and ability to take trips by each mode. The tools of microeconomics provide perhaps the most straightforward framework for such a discussion, by emphasizing how overall resource constraints enforce tradeoffs among available alternatives, such as travel modes, and how the relative attractiveness of those alternatives in turn depends on relative costs, such as trip times (e.g., Ben-Akiva and Lerman, 1985; Small, 1992).
To demonstrate the main results most clearly, we focus on just two components of travel behavior: Trip frequency and mode split. Consider the problem of individuals making choices over three uses of time: the number of trips they complete by car, those they complete by foot, and a composite good representing all other uses of time. For most purposes, a trip is a “derived” demand, meaning that people typically travel as a means to an end, not as an end in itself. A “trip” is thus defined as a hedonic index of the quantity and kinds of goods one obtains during each sort of trip.

Following Crane (1996b), the decision process behind the choice of the number of trips may be formalized as the constrained maximization problem of choosing the number of trips by each mode to maximize the benefit of travel by mode, subject to a budget constraint reflecting travel costs and available time. Say that individuals choose their desired number of trips by each mode to maximize

$$U(x, a, w)$$

subject to

$$y = x + ap_a + wp_w,$$

where $U$ is an index of the benefits of using time for each purpose, $a$ is a vector of the number of trips by automobile for each purpose, $w$ is a vector of the number of trips by walking for each purpose, the $p_i$ are the respective vectors of times for each trip type in each mode ($i = a, w$), and $y$ is total available time. The time per trip is the quotient of trip length $m_i$ and speed $t_i$; i.e., where $p_i = m_i / t_i$ for $i = a, w$, for any particular trip purpose. Note that the prices in this problem are themselves often choice variables, an obstacle to measuring demand that we will try to finesse statistically below.

---

5 The model abstracts from other decisions, which is different from assuming they do not happen but does imply they are not a central feature of the story. We also ignore non-time constraints to emphasize the restriction imposed by the time required for a trip in each mode on the choice of the number of trips in each mode.

6 The formal statement of the maximization problem should properly include certain conditions on the form of preferences, price-taking behavior, and optimization over other consumption; e.g., see Kreps (1990). It is assumed the standard and necessary conditions hold.
The solution to the trip choice problem is summarized by the trip demand functions \( a(p_a, p_w, y) \) and \( w(p_a, p_w, y) \). The practical value of these demand functions is that they permit "predictions" of how changes in trip times in each mode interact to determine the desired number of trips by mode. For example, once the problem has been solved for the demand functions, they can be used to estimate the impact of an urban design change that lowered the time (or other cost) of a trip by foot on both the number of trips by foot and the number of trips by car. This information could thus be used to calculate how vehicle miles traveled respond to increased pedestrian or auto access due to a change in street patterns. Estimable forms of these demand functions for empirical application to specific data may be obtained by specifying a particular form for \( U \).

Following the steps above, a demand functions for car trips should express demand as a function of relative prices. Unfortunately, the data are not in a form that permits all prices to be observed for each household, or even for each trip. Since the “price” of a walking trip is the length of trip, and so few households reported taking walking trips, the demand for car travel in particular cannot be estimated as a function of the price of travel by foot.\(^7\) As a result, we assume preferences take the familiar Cobb-Douglas form, yielding demand functions of the form:\(^8\)

\[
a(p_a, y, \tau) = \frac{\alpha y^\tau}{p_a}
\]

where \( \alpha \) is the taste parameter and \( \tau \) is the shift parameter reflecting, in this case, a land use feature.

Trips are not a homogeneous commodity at the household or person level. Each trip has a different length and speed. For the demand functions estimated below, the median trip distances and median trip speed for each household, by mode, were used as the trip own-price variables. For the

\(^7\) Each potential trip faced by a potential traveler therefore has a distinct price. The specification below estimates the demand for a trip of a given length by a particular mode.

\(^8\) Cobb-Douglas preferences are the simplest and most widely used functional specification that allows for continuously varying marginal rates of substitution and satisfies all the desirable properties of preference relations required for “well behaved” demand functions (see, e.g., Deaton and Muellbauer, 1980).
household-level model, resources were measured by reported household income category. Income was reported as a categorical variable for three categories only; the highest was used as the excluded category in the regressions below. Available taste variables included household size (HHSZ), type of housing unit (SFR=1 if a detached single family dwelling) and housing tenure (TENURE=1 if owner-occupied). Finally, land use variables included neighborhood street pattern, described earlier, the proportion of land in the household’s census tract that was residential (RES_O), commercial (COMM_O) or vacant (VACANT_O), and the distance of the trip origin from the central business district (D_CBD) as well as that same distance squared (DIST_2) which accounts for distance decay, or nonlinearity in that distance.9

Table 6 gives the results of ordered logit regressions of each household's total nonwork car trips on price, resource, taste and land use variables, for those who took such trips.10 The price variables, normally excluded in other studies, are significant and have the expected signs. The median length of car trips for the household is significantly negative; that is, the longer trips are, on average, the fewer are taken. The median trip speed is significantly positive so that, controlling for length, more trips are associated with less time consuming trips, on average. Among land use variables, the proportion of vacant and undeveloped land uses in the household's census tract is significantly negative with 94% confidence. Increases in vacant and undeveloped land uses are associated with fewer non-work car trips for the household when controlling for other factors. This result must be explained by factors other than trip distance. That is, increases in vacant land suggest fewer car trips, but those trips are not necessarily longer trips to compensate for the isolated nature of the trip's origin.

---

9 The linear distance measure is meant to be a proxy for neighborhood age and density, assuming that newer and more suburban neighborhoods are more distant from the Central Business District (which in this case is measured from the intersection of 4th Avenue and B Street, per the practice of the California Department of Transportation).

10 The model was estimated by both ordered logit and two-stage least squares. When using a discrete ordered dependent variable such as the number of trips taken by a household (or person), the choice is easy as the ordered logit framework allows for an unbiased estimation in comparison to ordinary least squares (Kennedy 1992). Yet the price variables are clearly endogenous based both on theory and the results of Hausman tests for specificity. By using two-stage least squares the price variables were instrumented, but not to our satisfaction with the variables available in the data. These estimation issues should be revisited as more complete data sets become available.
Note that having trips originate in a connected street network (GRID=1) neighborhood has no significant influence on the number of trips relative to cul-de-sac networks (the excluded category for this group of street network dummy variables), although there are *more* trips originating in mixed street pattern areas. The remaining street network variable identifying dense street patterns (HEAVY) is associated with *fewer* car trips relative to less dense networks, consistent with other studies. And similarly consistent with the literature, distance from the central business district is associated with more car trips. In addition, household size and home ownership are significantly positive. The latter may capture in part the role of higher income in generating trips.

[Table 6 is on page 26.]

Not reported here, but giving similar results, are models restricted to shopping trips only to control for trip purpose. They fit well though fewer variables are significantly different from zero. We also restricted the sample to trips of less than 2 miles and trips of less than 5 miles, to emphasize the role of land use and street patterns near the trip origin. Finally we estimated similarly specified models of walking trips. In none of these were the street network variables significant.

A second set of models estimated car trip frequency for working age persons (ages 16 through 64) as an attempt to disaggregate the choices made at the household level. By selecting only working age travelers we are avoiding the influence of double counting the trip made, say, by a parent taking a child to soccer practice (indeed, who is the decision maker here?). By focusing on the person, we can observe the influence of factors not available at the household level such as gender (where MALE=1 if so), AGE, if a person is a full-time worker (FULLTIME) and possesses a driver's license (DRLIC). The price variables are similar to those in the household file, except they summarize the trips made by the person rather than the household.
Table 7 (on page 27) presents the results of the person-level analysis. As expected, the speed price variable is positively associated with trip frequency while the length price variable shows a negative association. Male gender is negatively associated with trip frequency, suggesting that women are more likely to engage in non-work travel, as expected. Also expected is that full-time work status is negatively associated with trip frequency, suggesting that full-time workers have less opportunity to conduct non-work travel. None of the street network characteristics are statistically significant. Street density is also insignificant. However, the proportion of commercial land uses in the origin tract (COMM_O) is positively associated with trip generation and the proportion of vacant land in the origin tract shows a negative association. This finding suggests that more mixed use — larger shares of commercial use in residential areas — may generate more nonwork automobile trips when controlling for other factors in this sample.

As with the household level model, a similar model was estimated only for shopping trips taken by car. Again, trip speed is positively associated with the number of shopping trips, trip distance is negatively associated as was full-time work status and the number of adults in the household. None of the street network or land use variables are statistically significant.

A third set of models examined the decision to travel by car or by foot. These were specified much as the trip frequency models: As a function of trip prices, resources, taste variables, and land use variables. Table 8 thus explains mode split between automobile and other travel on data disaggregated to the trip level (rather than aggregated up to the household or person level as above). It estimates a probit equation of the decision to drive (CARTRIP=1) versus the decision to walk, at the trip level. The length and speed of the trip are both positively related to car use, as expected. The probability of using a car for a given trip is greater the distance of the origin from downtown San Diego, and greater the age of the traveler. The probability of using a car is lower the more vacant and
undeveloped land in the origin census tract. There is no evidence that street network variables play a significant role in the choice of a car for travel in our sample.\textsuperscript{11} 

[Table 8 is on page 28.]

4. Conclusion

The influential literatures of neotraditional planning and the “new urbanism” often argue that car use will decline in neighborhoods designed with more pedestrian friendly features, such as a connected street layout, more mixed use, high enough densities to more closely group some commercial and residential development, traffic calming, and so on. Many times, these transportation benefits have been advertised as facts rather than hypotheses, and have even been utilized or at least recommended as tools for decreasing the negative environmental impacts associated with car travel.

From a research perspective the big question at hand is how urban form affects travel behavior. The most straightforward answer is that we know quite little; most research has estimated \textit{ad hoc} models, avoiding the kind of systematic behavioral analysis that would allow us to compare different situations with different features in a generalizable manner. Simply including population density or the number of four-way intersections on the right-hand side of an intuitively specified regression model doesn't tell us much about how to interpret their measured impact, or how these features interact. In addition, the common use of aggregate data or engineering simulations derived from unrealistic assumptions has tended to generate more questions than answers. What we want, in principle, is to understand first how behavior responds to standard behavioral variables such as prices, resources and preferences, and then second how different elements of urban form correspond

\textsuperscript{11} The same variables are significant, with the same sign, when the sample is restricted to trips of less than 2 miles in length. Only the speed of the trip is significant in this model estimated for shopping trips alone. (These results are available from the authors on request.)
to prices, resources and preferences. This has not been done in earlier work, thus we have not been able to measure how responsive behavior is or isn't to consistently defined elements of the urban environment. Put another way, we have not yet thought much about how to measure the user demand for individual urban features.

We addressed this gap by applying a traditional demand framework to neighborhood land use and design elements, to our knowledge for the first time. The empirical model is thus based on the idea that trip behavior can be explained as a function of trip costs and benefits, which in turn are the product of trip lengths, modes, purposes, and individual characteristics. Within this framework our data do not generally support the argument that the neighborhood street pattern, the single most implemented traffic feature of the new urbanism, has any significant effect on car or pedestrian travel when controlling for land uses and densities around the trip origin, trip costs, and traveler characteristics. Note that our point does not depend on the applicability of these results to other communities. Other settings may reveal contrary data. Rather, our study suggests the need for careful attention to the particular circumstances of each design rather than the rhetoric of an otherwise intuitive and potentially attractive planning initiative. The new urbanism is, in many respects, an exciting and thoughtful planning trend. Nonetheless, it ought to be implemented with some care as the environmental benefits of each of its design elements have yet to be demonstrated.
References


### Table 1: Sample Mode Distribution

<table>
<thead>
<tr>
<th>Mode</th>
<th>Number of Trips</th>
<th>% of Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Auto</td>
<td>3,609</td>
<td>85.95%</td>
</tr>
<tr>
<td>Walk</td>
<td>369</td>
<td>8.79%</td>
</tr>
<tr>
<td>Other</td>
<td>221</td>
<td>5.26%</td>
</tr>
<tr>
<td>Total</td>
<td>4,199</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

### Table 2: Trip Characteristics by Residential Street Configuration at Trip Origin

<table>
<thead>
<tr>
<th>Street Pattern</th>
<th>Duration (in minutes)</th>
<th>Distance (in miles)</th>
<th>Speed (Miles per Hour)</th>
<th>Number of Trips</th>
<th>Proportion of Trips</th>
</tr>
</thead>
<tbody>
<tr>
<td>Grid</td>
<td>14.88</td>
<td>4.71</td>
<td>17.06</td>
<td>664</td>
<td>15.8%</td>
</tr>
<tr>
<td>Cul-de-sac</td>
<td>14.59</td>
<td>5.72</td>
<td>22.96</td>
<td>2,010</td>
<td>47.9%</td>
</tr>
<tr>
<td>Mixed</td>
<td>13.10</td>
<td>4.55</td>
<td>20.19</td>
<td>1,525</td>
<td>36.3%</td>
</tr>
<tr>
<td>Total</td>
<td>14.09</td>
<td>5.13</td>
<td>21.02</td>
<td>4,199</td>
<td>100.0%</td>
</tr>
</tbody>
</table>
### Table 3: Testing for Difference in Mean Car Trip Distance (in miles)

<table>
<thead>
<tr>
<th>Neighborhood Type</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cul-de-sac</td>
<td>6.10</td>
<td>7.87</td>
<td>1,748</td>
</tr>
<tr>
<td>Grid</td>
<td>5.23</td>
<td>7.80</td>
<td>536</td>
</tr>
</tbody>
</table>

$H_0$: $\text{mean(cul-de-sac)} = \text{mean(grid)}$

$t = 2.26$ with 2,282 df $\Rightarrow$ reject $H_0$ with 95% confidence

### Table 4: Testing for Difference in Mean Trip Speed (miles per hour)

<table>
<thead>
<tr>
<th>Neighborhood Type</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cul-de-sac</td>
<td>24.43</td>
<td>14.00</td>
<td>1,748</td>
</tr>
<tr>
<td>Grid</td>
<td>19.13</td>
<td>12.13</td>
<td>536</td>
</tr>
</tbody>
</table>

$H_0$: $\text{mean(cul-de-sac)} = \text{mean(grid)}$

$t = 9.47$ with 2,672 df $\Rightarrow$ reject $H_0$ with 99% confidence

### Table 5: Testing for Difference in Mean Number of Car Trips per Household

<table>
<thead>
<tr>
<th>Neighborhood Type</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cul-de-sac</td>
<td>2.57</td>
<td>2.74</td>
<td>679</td>
</tr>
<tr>
<td>Grid</td>
<td>2.08</td>
<td>2.27</td>
<td>258</td>
</tr>
</tbody>
</table>

$H_0$: $\text{mean(cul-de-sac)} = \text{mean(grid)}$

$t = 2.59$ with 935 df $\Rightarrow$ reject $H_0$ with 99% confidence
Table 6: Ordered Logit Regression of Daily Household Car Trip Frequency

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Estimated coefficient</th>
<th>Standard error</th>
<th>z statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>price variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>median car trip length ((mdcmile))</td>
<td>-.0594</td>
<td>.0096</td>
<td>-6.163</td>
</tr>
<tr>
<td>median car trip speed ((mdcmph))</td>
<td>.0808</td>
<td>.0054</td>
<td>14.962</td>
</tr>
<tr>
<td><strong>land use variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>connected street pattern ((grid))</td>
<td>.3232</td>
<td>.1680</td>
<td>1.924</td>
</tr>
<tr>
<td>mixed street pattern ((mixed))</td>
<td>.2530</td>
<td>.1168</td>
<td>2.165</td>
</tr>
<tr>
<td>street network density ((heavy))</td>
<td>-.2394</td>
<td>.1168</td>
<td>-2.050</td>
</tr>
<tr>
<td>residential share of census tract ((res_o))</td>
<td>.0011</td>
<td>.3215</td>
<td>0.003</td>
</tr>
<tr>
<td>commercial share of tract ((comm_o))</td>
<td>.5374</td>
<td>.7284</td>
<td>0.738</td>
</tr>
<tr>
<td>vacant share of census tract ((vacant_o))</td>
<td>-.7633</td>
<td>.3957</td>
<td>-1.929</td>
</tr>
<tr>
<td>distance to downtown ((d_cbd))</td>
<td>.0514</td>
<td>.0190</td>
<td>2.696</td>
</tr>
<tr>
<td>squared distance to downtown ((dist_2))</td>
<td>-.0011</td>
<td>.0005</td>
<td>-2.526</td>
</tr>
<tr>
<td><strong>household resource &amp; taste variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>income less than $20,000 ((inc0_20))</td>
<td>-.2266</td>
<td>.1548</td>
<td>-1.463</td>
</tr>
<tr>
<td>income is $20,000 to $40,000 ((inc20_40))</td>
<td>.1488</td>
<td>.1125</td>
<td>1.322</td>
</tr>
<tr>
<td>mean household age ((mn_age))</td>
<td>.0246</td>
<td>.0037</td>
<td>6.603</td>
</tr>
<tr>
<td>number of children ((kids))</td>
<td>.3747</td>
<td>.0906</td>
<td>4.135</td>
</tr>
<tr>
<td>household size ((hhsz))</td>
<td>.7631</td>
<td>.0667</td>
<td>11.428</td>
</tr>
<tr>
<td>housing tenure ((tenure))</td>
<td>.2684</td>
<td>.1298</td>
<td>2.068</td>
</tr>
<tr>
<td>housing type ((sfr))</td>
<td>-.2182</td>
<td>.1215</td>
<td>-1.796</td>
</tr>
</tbody>
</table>

n = 1,336
Pseudo R\(^2\) = 0.13
Log Likelihood = -2456.35
\(\chi^2 = 744.00\)

Note: Coefficients in boldface are significant with 95% confidence.
Table 7:  
Ordered Logit Regression of Car Trip Frequency for Persons Aged 16-64

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Estimated coefficient</th>
<th>Standard error</th>
<th>z statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>price variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>car trip length ((cmiles))</td>
<td>-.0758</td>
<td>.0099</td>
<td>-7.656</td>
</tr>
<tr>
<td>car trip speed ((cmph))</td>
<td>.1304</td>
<td>.0052</td>
<td>25.080</td>
</tr>
<tr>
<td><strong>land use variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>connected street pattern ((grid))</td>
<td>.0937</td>
<td>.1512</td>
<td>0.619</td>
</tr>
<tr>
<td>mixed street pattern ((mixed))</td>
<td>.1570</td>
<td>.1047</td>
<td>1.499</td>
</tr>
<tr>
<td>street network density ((heavy))</td>
<td>-.0690</td>
<td>.1057</td>
<td>-0.653</td>
</tr>
<tr>
<td>residential share of census tract (res_o)</td>
<td>.0159</td>
<td>.2844</td>
<td>0.056</td>
</tr>
<tr>
<td>commercial share of tract (comm_o)</td>
<td>1.4355</td>
<td>.6985</td>
<td>2.052</td>
</tr>
<tr>
<td>vacant share of census tract (vacant_o)</td>
<td>-.6863</td>
<td>.3500</td>
<td>-1.961</td>
</tr>
<tr>
<td>distance to downtown ((d_cbd))</td>
<td>.0035</td>
<td>.0185</td>
<td>0.189</td>
</tr>
<tr>
<td>squared distance to downtown ((dist_2))</td>
<td>.0001</td>
<td>.0005</td>
<td>0.063</td>
</tr>
<tr>
<td><strong>household resource &amp; taste variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>income less than $20,000 (inc0_20)</td>
<td>-.0716</td>
<td>.1524</td>
<td>-0.470</td>
</tr>
<tr>
<td>income is $20,000 to $40,000 (inc20_40)</td>
<td>.1046</td>
<td>.1051</td>
<td>0.995</td>
</tr>
<tr>
<td>age of traveler ((age))</td>
<td>.0114</td>
<td>.0047</td>
<td>2.414</td>
</tr>
<tr>
<td>mean household age (mn_age)</td>
<td>-.0164</td>
<td>.0048</td>
<td>-3.423</td>
</tr>
<tr>
<td>male</td>
<td>-2.307</td>
<td>.0948</td>
<td>-2.434</td>
</tr>
<tr>
<td>has a driver’s license (drlic)</td>
<td>1.0631</td>
<td>.2118</td>
<td>5.018</td>
</tr>
<tr>
<td>employed fulltime (fulltime)</td>
<td>-1.0583</td>
<td>.1038</td>
<td>-10.197</td>
</tr>
<tr>
<td>housing tenure (tenure)</td>
<td>.2218</td>
<td>.1196</td>
<td>1.855</td>
</tr>
<tr>
<td>number of cars in household (cars)</td>
<td>-.0367</td>
<td>.0527</td>
<td>-0.696</td>
</tr>
<tr>
<td>number of adults in household (adults)</td>
<td>-.0177</td>
<td>.0640</td>
<td>-0.277</td>
</tr>
<tr>
<td>housing type (sfr)</td>
<td>.0303</td>
<td>.1204</td>
<td>0.251</td>
</tr>
</tbody>
</table>

\(n = 2,144\)

Pseudo R\(^2\) = 0.24

Log Likelihood = -2113.47

\(\chi^2 = 1355.01\)
Table 8: Probit Regression of Travel Mode Choice (Car = 1)

<table>
<thead>
<tr>
<th>Explanatory variable</th>
<th>Estimated coefficient</th>
<th>Standard error</th>
<th>z statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>price variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>trip length (miles)</td>
<td>.2697</td>
<td>.0528</td>
<td>5.111</td>
</tr>
<tr>
<td>trip speed (mph)</td>
<td>.0603</td>
<td>.0084</td>
<td>7.174</td>
</tr>
<tr>
<td><strong>land use variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>connected street pattern (grid)</td>
<td>.1317</td>
<td>.1686</td>
<td>0.781</td>
</tr>
<tr>
<td>mixed street pattern (mixed)</td>
<td>.0046</td>
<td>.1214</td>
<td>0.038</td>
</tr>
<tr>
<td>street network density (heavy)</td>
<td>-.1867</td>
<td>.1272</td>
<td>-1.468</td>
</tr>
<tr>
<td>residential share of census tract (res_o)</td>
<td>-.0935</td>
<td>.3514</td>
<td>-0.266</td>
</tr>
<tr>
<td>commercial share of tract (comm_o)</td>
<td>-.1606</td>
<td>.6719</td>
<td>0.239</td>
</tr>
<tr>
<td>vacant share of census tract (vacant_o)</td>
<td><strong>-0.9594</strong></td>
<td>.4408</td>
<td><strong>-2.177</strong></td>
</tr>
<tr>
<td>distance to downtown (d_cbd)</td>
<td>.0711</td>
<td>.0192</td>
<td>3.705</td>
</tr>
<tr>
<td>squared distance to downtown (dist_2)</td>
<td>-.0017</td>
<td>.0005</td>
<td>-3.655</td>
</tr>
<tr>
<td><strong>household resource &amp; taste variables</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>income less than $20,000 (inc0_20)</td>
<td>.2482</td>
<td>.1454</td>
<td>1.708</td>
</tr>
<tr>
<td>income is $20,000 to $40,000 (inc20_40)</td>
<td>.1611</td>
<td>.1196</td>
<td>1.347</td>
</tr>
<tr>
<td>age of traveler (age)</td>
<td><strong>.0117</strong></td>
<td><strong>.0042</strong></td>
<td><strong>2.767</strong></td>
</tr>
<tr>
<td>number of drivers (drivers)</td>
<td>-.0030</td>
<td>.0514</td>
<td>-0.059</td>
</tr>
<tr>
<td>housing tenure (tenure)</td>
<td>.1773</td>
<td>.1233</td>
<td>1.438</td>
</tr>
<tr>
<td>male</td>
<td>.1847</td>
<td>.1078</td>
<td>1.713</td>
</tr>
</tbody>
</table>

n = 2,326  
Pseudo R^2 = 0.13  
Log Likelihood = -379.22  
\( \chi^2 = 354.05 \)

Note: Coefficients in boldface are significant with 95% confidence.
Figure 1:
Location of Sample Households in San Diego County
Example of "Grid" Neighborhood in San Diego Data