The Effect of Density and Trip-Chaining on the Interaction between Urban Form and Transit Demand

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Abstract

Some urban policies are designed to reduce auto and increase transit usage. Evidence is mixed because most empirical research uses *ad hoc* specifications. We estimate empirical models of the interaction between urban form and transit demand drawn from urban economic theory. Population density has a small impact on transit demand, which decreases when residential location is endogenous. Households living farther from work use less transit, a result of trip-chaining. Reducing the spatial allocation of non-work activities, improving transit accessibility at and around subcenters, and increasing the presence of retail locations in proximity to transit-oriented households would increase transit demand.

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1.0 Introduction

Recently urban policies have sought to reduce presumed inefficiencies associated with urban sprawl. Since it is assumed the auto is the main cause of urban sprawl (Glaeser and Khan, 2004), the policies are intended to produce a more compact urban area, which would presumably reduce auto usage and increase transit usage. Evidence favorable to such policies is mixed. This is so, we think, because most empirical research is based on *ad hoc* empirical specifications, lacking a behavioral framework that considers travel as the result of activities planned and executed through space and time. To address this shortcoming, we present models of the interaction between urban form and transit demand drawn from urban economic theory. The theoretical hypotheses are empirically tested using a dataset that integrates travel and land-use.

We find that population density does not have a large impact on transit demand and that the effect decreases when residential location is made endogenous. When population density and residential location are jointly endogenous, the elasticity of transit demand with respect to walking distance to a transit station increases over the case in which these variables are treated as exogenous. We find that households living farther from work use less transit due to trip-chaining. Households living far from work engage in complex trip chains and have a more dispersed activity space, which requires reliance on more flexible modes of transportation. Reducing the spatial allocation of non-work activities and improving transit accessibility at and around subcenters would increase transit demand. Similar effects may be obtained by increasing the presence of retail locations in proximity to transit-oriented households.

2.0 Motivation

In the last decade, over fifty empirical studies have examined the linkages between urban form and travel behavior. Crane (2000), Badoe and Miller (2000), and Ewing and Cervero (2001) summarize the most relevant empirical work. Most of this research involves regression of various measures of travel behavior on residential and employment density, while controlling for travelers' demographic characteristics. These studies have led to the conclusion that policy interventions to increase density are capable of reducing automobile use (Burchell et al., 1998; Cao, Mokhtarian and Handy, 2006; Ewing, 1997). Nevertheless, criticism has centered on *ad hoc* specifications and omitted-variable bias. The former is due to lack of a theoretical foundation for the empirical work, and the latter is due to likely simultaneity and endogeneity in the relationship between urban form and travel (Badoe and Miller, 2000).

The influence of urban form on travel behavior is complicated by the evolution of the built environment, which might lead to residential self-sorting. *Self-sorting* refers to factors that induce households to choose a residential location, in part, due to idiosyncratic preferences for travel and location. If residential self-sorting is not accounted for, empirical findings overstate the efficacy of policies to affect travel behavior by changing the built environment. Mokhtarian and Cao (2008) provide a comprehensive review of empirical work on residential self-sorting. Although researchers recognize that idiosyncratic preferences for travel and location affect residential location, there is disagreement on how best to handle such preferences, which, if ignored, result in omitted-variable bias. The empirical treatment of omitted-variable bias in this context ranges from nested logit models (Cervero, 2007) to sophisticated error-correlation models (Bowes and Ihlanfeldt, 2001; Pinjari et al., 2007) and two-part models (Vance and Hedel, 2007). Following Bhat and Guo (2004), Pinjari *et al*. (2007) propose a model jointly determining residential location and mode choice in which both choices influence each other through observed and unobserved individual taste heterogeneity. Findings suggest that, after accounting for self-sorting, the built environment affects commute mode-choice behavior.

Treating mode choice and residential location in this framework does not, however, remove the *ad hoc* determination of the residential choice set. For example, both Pinjari *et al*. (2007) and Bhat and Guo (2004), who adopt a multinomial logit-ordered structure that explicitly considers the correlation of unobserved factors simultaneously affecting both choices, must determine *a priori* the location choice set. Furthermore, in simultaneous equation modeling or instrumental variable regression, the validity of results hinges on determination of the exclusion restrictions. Exclusion restrictions should be based on sound behavioral theory (Wooldridge, 2002). Nevertheless, in all studies of residential self-sorting employing simultaneous-equation techniques, including the work of Bagley and Mokhtarian (2002), Handy *et al*. (2005), and Cao *et al*. (2007), there is no explicit treatment of exclusion restrictions drawn from a formalized theoretical framework.

Moreover, studies employing activity-based modeling fail to account properly for endogeneity. In addition, empirical work is lacking on the relationship between urban form and travel behavior that accounts for trip-chaining. *Activity-based* modeling is characterized by a focus on patterns or sequences of behavior instead of discrete trips (Jones, Koppelman and Orfeuil, 1990). This framework is better suited than was previous work analyzing the impact of land use on travel patterns because it acknowledges trip-chaining. A *trip chain* is defined as a sequence of trips that starts from home and/or ends at home.

In sum, there is no empirical work accounting for the joint determination of residential location, trip-chaining, the area of non-work activities, and socio-demographic differences among individuals, with a theoretical foundation based on the tradeoff between commuting and non-work travel. This paper attempts to fill this gap in the literature. We formulate three models of increasing generality. The purpose is to show how endogenizing relevant variables changes the results obtained by others.

3.0 Theory

3.1 Variables drawn from theory

Economic analysis of the interaction between residential and work locations began with Alonso (1964) and Muth (1969). In a budget-constrained, utility-maximization framework, the theory determines residential location as the result of a tradeoff between housing and transportation expenditures, given tastes, income, housing price, and transportation costs, in which all transportation for work and non-work activities is to the central business district (CBD) of the urban area. Individuals locate at a distance at which the marginal cost of transportation equals the marginal housing cost savings obtained by a move farther from the CBD.

We retain this tradeoff but assume it occurs in a polycentric urban area, rather than a monocentric one. In this, we follow Anas and Kim (1996) and Anas and Xu (1999). We implement this idea by defining residential location as the *job-residence pair* (*RL*) in an urban area in which jobs and residences are dispersed. This definition of residential location differs from that used in the current literature. Some researchers have considered residential location as a choice to reside within a geographical unit, such as a traffic assignment zone (Bhat and Guo, 2004; Pinjari et al., 2007). Others have used transit proximity as a proxy for residential location (Cervero, 2007). Although these usages are dictated by the need to distinguish the influence of the built environment from that of self-sorting, they are not based on a theory of residential location. For the variables affecting *RL*, we use household income (*inc*), median house price (*hprice*), and, as proxies for transportation cost, distance between home and the CBD (*cbd_dist*) and distance between home and the nearest subcenter (*subc_dist*). The use of distance measures as controls in multivariate analysis of transit travel behavior is a common practice (Cervero and Wu, 1998; Kuby, Barranda and Upchurch, 2004; Pushkarev and Zupan, 1977; Pushkarev and Zupan, 1982; Zupan and Cervero, 1996).

We assume the location decision is based in part on idiosyncratic preferences for location and travel, which relaxes the assumption of common tastes in earlier models. To capture idiosyncratic preferences, we use house age (*hage*), number of rooms (*rooms*), and tenure choice, that is, whether the household is a renter or an owner (*own*). These variables control for housing preferences not directly affecting travel behavior but directly affecting the residential choice decision. To control for neighborhood characteristics, we include the percentage of households living below the poverty line (*pov*) and a diversity index (*div*). The former serves as a proxy for crime, while the latter is an index of ethnic heterogeneity that varies from zero (only one race in the neighborhood) to one (no race is prevalent), similar to Shannon's diversity index. The Shannon index compares diversity between habitat samples in terms of the proportion of individuals of a given species in the set (see Begon, Harper, and Towsend (1996) for a review).

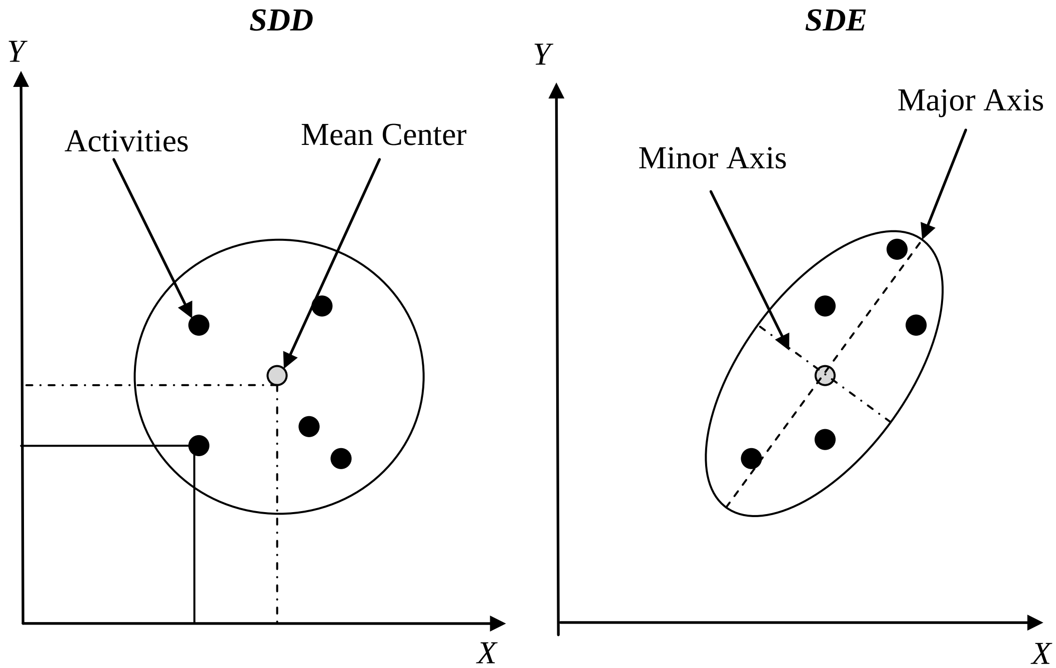
Of these variables, house age has been used before as an instrumental variable in multivariate regression studies that considered travel behavior as endogenous to urban form (Boarnet and Crane, 2001; Boarnet and Sarmiento, 1998; Crane, 2000; Crane and Crepeau, 1998a; Crane and Crepeau, 1998b), while the remaining ones are unique to this study although controls for neighborhood characteristics have been used elsewhere. For example, the proportion of block-group or census-tract population that is Black and the proportion Hispanic have been used as instruments by Boarnet and Sarmiento (1998) and the percent of foreigners by Vance and Hedel (2007).

In addition to determining residential location in a polycentric urban area, Anas' theory also determines the sequence of non-work trip chains. To capture non-work trip chains, we use variables to control for factors affecting both the spatial extent of non-work activities and the ensuing travel behavior, specifically, travel time (*act_tt*) and the duration of non-work activity (*act_dur*). These variables are commonly used in the activity-based literature in modeling activity duration and scheduling (Bhat, 1997; Bhat, 1999; Bhat, 2001; Bhat and Guo, 2004) and activity travel patterns (Kuppam and Pendyala, 2001).

We account for the effect of the built environment on the spatial dispersion of out-of-home activities by introducing the variable *activity space* (*AS*). There are several ways to measure the activity space. The simplest measure is represented by the standard distance deviation (SDD), calculated as a standardized distance of out-of-home activities from a mean geographic center. The mean activity center is analogous to the sample mean of a dataset, and it represents the sample mean of the *x* and *y* coordinates of non-work activities contained in each household activity set. Interpretation is relatively straightforward: a larger SDD indicates greater spatial dispersion of activity locations. Ebdon (1977) notes, however, this measure is adversely affected by the presence of outliers. As a result of squaring all the distances from the mean center, the extreme points have a disproportionate influence on the value of the standard distance. To attenuate this problem, we have chosen the standard distance ellipse (SDE), using the formula described in Levine (2005). These measures are illustrated in Figure 1.

Figure 1

Standard Distance Circle and Standard Distance Ellipse



Densely populated urban areas exhibit clustered activity locations, thus shrinking the size of the activity space, while the opposite is the case for less densely populated areas. This affects the spatial allocation of activities, which affects the demand for travel. Recent research finds that households residing in decentralized, lower-density urban areas have a more dispersed travel pattern than their counterparts residing in centralized, high-density urban areas (Buliung and Kanaroglou, 2006; Maoh and Kanaroglou, 2007).

Trip-chaining (*TC*) describes how travelers link trips between locations within an activity space. A trip from home to work with an intermediate stop to drop off children at day care is an example of a trip chain. Drawing on Anas (2007), we assume that the activity space results from utility-maximizing behavior determining non-work travel. As income increases, so does the demand for travel. Anas (2007) assumes individuals have preferences for heterogeneity in consumption. Individuals prefer to visit different locations, a behavior that positively affects the size of the activity space. Trip-chaining occurring on the home-job commute pair saves time. This time-saving in turn can be allocated either to additional non-work travel, thus increasing the overall demand for travel, or to a longer commute.[1] The positive relationship between more complex trip chains and the home-work commute is confirmed by empirical work (Bhat, 1997; Bhat, 2001; Davidson, 1991; Kondo and Kitamura, 1987; McGuckin and Murakami, 1999; Strathman, 1995). To capture variables affecting trip-chaining, we use the number of school-age children (*sch*), the number of vehicles owned by the household (*veh*), and the number of retail establishments (*r_est*) in the activity space.

We define travel demand (*TD*) as the number of work and non-work transit trips at the household level, a usage that departs from that of other researchers. For example, Boarnet and Crane (2001) assume that trip demand is either directly affected by land use or indirectly by influencing the cost of travel. In our models, land use (which we proxy with population density, *D*) directly affects the spatial allocation of activities.

Our measure of transit-station proximity (*walk_dist*) differs from that used elsewhere. Proximity is usually measured as the radius of a circular buffer around a station. Cervero (2007), for example, used a half-mile radius. This measure of transit proximity fails to account for barriers that prevent access to a station located within the radius, which is why we use walking distance from the residence to the nearest transit station. Empirical studies on the relevance of transit station proximity to transit patronage show a strong relationship between transit use and station proximity (Cervero, 2007; Cervero and Wu, 1998). We also include the following

[1] Leisure time is another possibility, but that variable is not included in Anas (2007).

measures of transit supply to account for the presence of a transit stop near the workplace (*tswork*), the supply of park-and-ride facilities near a transit stop (*prkride*), and the presence of a transit-oriented development (*ts_tod*) near the residential unit.

3.2 The general model

These variables are brought together in the following general model (theoretically endogenous variables are in upper case letters, while exogenous variables are in lower case).

$$TC = TC\left(AS, RL, walk\_dist, veh, act\_tt, act\_dur, sch, subc\_dist\right) \tag{1}$$

$$AS = AS\left(TC, D, act\_dur, inc, r\_est\right) \tag{2}$$

$$TD = TD\left(TC, AS, RL, walk\_dist, tswork, prkride, ts\_tod, veh\right) \tag{3}$$

$$RL = RL\left(TC, TD, hprice, hage, rooms, div, pov, own\right) \tag{4}$$

$$D = D\left(RL, AS, subc\_dist, cbd\_dist\right). \tag{5}$$

Equation (1) describes trip-chaining behavior occurring on the commute trip. Trip-chaining, jointly determined with the activity space (*AS*) and residential location (*RL*), is affected by transit-station proximity (*walk_dist*), vehicle availability (*veh*), travel behavior (*act_tt* and *act_dur*), number of school-age children (*sch*), and the distance between home and the nearest subcenter (*subc_dist*).

Equation (2) describes how the spatial extent of non-work activities (*AS*) responds to changes in urban form, being jointly determined with trip-chaining (*TC*) and urban form (*D*). The activity space responds to the duration of non-work activities (*act_dur*), household income (*inc*), and retail establishment concentrations (*r_est*).

Equation (3) describes the demand for transit trips (*TD*), due to non-work travel, which is jointly determined with trip-chaining (*TC*), the activity space (*AS*), and residential location (*RL*). Transit-station proximity (*walk_dist*) and the presence of a nearby transit stop (*tswork*) and of a park-and-ride facility (*prkride*) at the workplace also determine transit demand. To test the efficacy of transit-oriented-development policies in affecting ridership, we include the presence of a transit-oriented development near the residential unit (*ts_tod*). Finally, the number of autos at the disposal of the household (*veh*) also determines transit demand.

Equation (4) describes residential location (*RL*), jointly determined with trip-chaining (*TC*) and transit demand (*TD*). We consider housing characteristics—pricing (*hprice*), age (*hage*), size (*rooms*), and tenure choice (*own*)—as factors affecting residential location, in addition to neighborhood characteristics, diversity (*div*), and poverty (*pov*).

Equation (5) describes population density (*D*), as jointly determined with residential location (*RL*) and the activity space (*AS*). In addition, the equation introduces variables serving as proxies for centrality dependence (*cbd_dist*) and for polycentricity (*subc_dist*).

3.3 Versions of the model for estimation

Equations (1)–(3) constitute Model I, which treats residential location and density as exogenous. Given these variables, the model jointly defines the activity space and the trip chain, which, in turn, determine travel demand, given consumption and location decisions. This may be interpreted as a short-run model in that residential location and density are predetermined.

Model II comprises Equations (1)–(4). In this extension, we relax the assumption of exogenous residential location. Treated as a choice variable, residential location is the outcome of a tradeoff between transportation and housing costs. Accounting for idiosyncratic preferences for transportation and location, households choose an optimal home-work commute, while optimizing non-work trip-chaining and the activity space, which, in turn, determine transit demand. This may be interpreted as an intermediate-run model in that residential location is endogenous while density is exogenous.

Model III is composed of Equations (1)–(5). In Equation (5) population density is endogenous. Exogenous variables serve as proxies for centrality dependence (*cbd_dist*) and for polycentricity (*subc_dist*). [2] This may be interpreted as a long-run model in that it treats density (urban form) as endogenous.

4.0 Data

We use travel-diary data from the 2000 Bay Area Travel Survey (BATS2000). BATS2000 is a large-scale regional household travel survey conducted in the nine-county San Francisco Bay Area of California by the Metropolitan Transportation Commission (*Household Travel Survey Data & Reports*, 2008). Completed in the spring of 2001, BATS2000 provides consistent and rich information on travel behavior of 15,064 households, with 2,504 households that make regular use of transit.[3]

Household activity locations are those visited by surveyed household members during a specified period, in this case two representative weekdays. BATS2000 reports the longitude and latitude of each activity. Using geographic information systems (GIS), we geocoded to the street address or street intersection 99.9 percent of home addresses and 80 percent of out-of-home activities, giving us precise locations of non-work activities, jobs, and residences.

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[2] Endogeneity tests led to *cbd_dist*, *subc_dist*, and *r_est* being treated as endogenous in Model III.

[3] In MTC usage, a transit household has one or more members using transit at least once during the two-day surveying period.

Using GIS spatial matching procedures, we combined BATS2000 travel data with geographical data from the U.S. Census Bureau Summary File 3 and 2000 U.S. Census Bureau County Business Patterns (CBP), which gave us detailed social, economic, and housing characteristics at the block group level and variables related to non-residential land use, such as commercial densities. Table 1 contains the variable names, brief descriptions, and descriptive statistics.

5.0 Estimation

In the structural equations of the models, endogenous variables appear on the right-hand side. Consequently, estimation requires structural equation modeling (SEM). SEM is used to capture the causal influences of the exogenous variables on the endogenous variables and the causal influences of the endogenous variables on one another. In the transportation literature there exist several applications of SEM using cross-sectional data, for example, Pendyala (1998), Fuji and Kitamura (2000), and Golob (2000). Additional examples are discussed by Golob (2003). There are also studies of the causal relationships among travel behavior and urban form that are effectively represented in a structural equation framework (Cao, Mokhtarian and Handy, 2007; Guevara and Moshe, 2006; Mokhtarian and Cao, 2008; Peng et al., 1997).

5.1 Model I: Endogenous trip-chaining, activity space, and transit demand

In this specification, residential location (*RL*) and density (*D*) are exogenous. Given these variables, the model jointly determines the trip chain (*TC*), the activity space (*AS*), and transit demand (*TD*). The equations of Model I are estimated by three-stage least squares (3SLS). All three equations pass the rank condition for identification. Equation (1) is overidentified, and Equations (2) and (3) are just identified.[4] The results are given in Table 2. To ensure normality assumptions are met, some of the variables are entered in logs, namely, *AS*, *D*, and *walk_dist*.

Table 1

Variables and Descriptive Statistics

Variable	*Description*	*Mean*	*S.D.*	*Min.*	*Max.*
inc	*Household Income* (1 *if < $10k to15 if > $150k*)	10.34	3.45	1.00	15.00
sch	*Number of children pre-k to middle school*	0.65	0.98	0.00	7.00
veh	*Household vehicles, number*	1.85	0.95	0.00	9.00
own	*Housing tenure* (*1=own, 0=renter*)	0.69	0.46	0.00	1.00
walk_dist	*Walking distance to nearest transit station, miles*	0.31	0.37	0.00	3.00
tswork	*Transit stop near work* (*1 within 0.5 mile, 0 otherwise*)	0.25	0.43	0.00	1.00
prkride	*Park & ride lot near work* (*1 within 0.5 mi., 0 otherwise*)	0.07	0.25	0.00	1.00
ts_tod	*TOD stop near residence* (*1 within 0.5 mi., 0 otherwise*)	0.01	0.12	0.00	1.00
cbd_dist	*Residential unit distance to CBD, miles*	44.70	25.20	0.17	137.12
subc_dist	*Residential unit distance to nearest subcenter, miles*	2.89	2.36	0.01	38.39
r_est	*Retail establishment density (number/mile^2); zip code level*	22.51	55.91	0.00	1,281.74
hprice	*Median housing price, $; block group level*	399,591	204,767	0	1,000,001
hage	*Median housing age, year; block group level*	35.49	14.86	1.00	61.00
rooms	*Median number of rooms; block group level*	5.92	1.04	0.00	9.10
pov	*Proportion of households living below poverty level; block group level*	0.06	0.06	0.00	0.79
div	*Diversity index, 0=homogenous, 1= heterogeneous; block group level*	0.58	0.19	0.00	0.99
act_dur	*Non-work activity duration, minutes*	131.05	89.86	2.00	1,440
act_tt	*Travel time to non-work activity, minutes*	81.16	98.23	0.00	2,897
TC	*Stops on home-work route, number*	1.17	1.33	0.00	8.00
TD	*Household linked transit trips, number*	0.39	0.99	0.00	9.00
AS	*Household activity space, size of SDE; miles^2*	16.83	32.61	0.75	437.23
RL	*Distance home-work, miles*	10.52	9.81	0.00	79.38
D	*Gross population density, persons/mile^2*	9,144	11,065	0.00	172,400

[4] Details are in an unpublished appendix available on request.

Table 2

Regression Results for Model I

Equation	*Coefficient*	*p-value*
(1) Trip-chaining, TC		
AS	0.0648	0.6960
RL	0.0096	0.0160
walk_dist	–0.0570	0.0000
veh	–0.0793	0.0100
act_tt	0.0014	0.0010
act_dur	–0.0022	0.0000
subc_dist	0.0439	0.0000
sch	0.0778	0.0000
constant	1.2771	0.0000
(2) Activity space, AS		
TC	0.5863	0.0000
D	–0.0974	0.0000
act_dur	0.0001	0.6880
inc	0.0299	0.0000
r_est	–0.0022	0.0000
constant	1.7226	0.0000
(3) Transit demand, TD		
TC	–0.6548	0.0000
AS	–0.3002	0.0010
RL	–0.0057	0.0070
walk_dist	–0.0800	0.0000
tswork	0.3848	0.0000
prkride	–0.0737	0.1510
ts_tod	0.2063	0.0600
veh	–0.0456	0.0390
constant	–0.1256	0.2150

N= 8,229; $F_{TC}=49.3$; $F_{AS}=73.6$; $F_{TD}=122.1$

The joint determination of trip-chaining and the spatial extent of non-work activities relate to transit patronage as hypothesized in the Section 3. The presence of a transit stop at the workplace (*tswork*) positively affects transit demand, as does the presence of a TOD transit stop in proximity to the residence (*ts_tod*). The size of the activity space reduces as density increases, which, in turn, positively affects the demand for transit. At locations where non-work activities are more clustered, the need to engage in journeys requiring modes other than transit decreases, resulting in increased transit usage. This finding suggests that policies affecting the clustering of non-work activities, such as mixed land-use policies, are likely to significantly affect transit ridership levels. The relevance of this relationship is better appreciated, however, when residential location is endogenous.

To appreciate the magnitude of the estimated effects, Table 3 reports point elasticities of transit demand with respect to selected explanatory variables. Elasticities are evaluated at data means and, because the models involve at least three simultaneous equations, are complicated to calculate.[5]

Table 3

Selected Elasticities for Model I

Elasticity	*RL*	*D*	*walk_dist*	*subc_dist*	*r_est*	*tswork**	*ts_tod**
TC	0.090	–0.006	–0.051	0.113	–0.047	-	-
AS	0.062	–0.101	–0.035	0.077	–0.051	-	-
TD	–0.097	0.089	–0.079	–0.282	0.045	0.385	0.206

*Indicates a proportional change.

Table 3 shows that a 20-percent increase in gross population density (*D*), equal to about 1,830 persons per square mile, produces a 1.8-percent increase in transit demand (*TD*). A doubling of the average walking distance (*walk_dist*) to the nearest transit station, an increase from

[5]Two unpublished appendices are available on request that detail the comparative static analyses and the elasticity calculations.

0.3 miles to 0.6 miles, decreases transit demand by 7.9 percent; at about one mile, transit demand declines by 18.5 percent. The presence of a transit station within a half-mile of the workplace (*tswork*) increases transit demand by 38.5 percent. Living in proximity to a TOD transit station (*ts_tod*) increases transit demand by about 20.6 percent. There is a ridership bonus for proximity to a station with accessibility features to promote transit use. We find a negative elasticity between residential location (*RL*) and transit use. This is consistent with the hypothesis that households with longer commutes engage in more complex trip chains, which positively affect the spatial extent of non-work activities. With exogenously fixed transit supply, as the activity space expands, transit demand declines.

The results also show that transit demand is sensitive to the presence of nearby subcenters (*subc_dist*) or, in general, to decentralization. The negative elasticity shows that increased polycentricity adversely affects transit demand. The farther a household lives from a subcenter, the less it uses transit. A 50-percent increase in distance to a subcenter, from 2.9 to 4.3 miles, decreases transit demand by about 14.1 percent. This happens because households rely more on other modes to carry out complex trip chains, a finding confirmed by the elasticity of trip-chaining with respect to distance to the nearest subcenter. This result is consistent with the current literature on transit competitiveness and polycentric metropolitan regions. For example, Casello (2007) finds that transit improvements between and within subcenters are necessary to realize the greatest improvements in transit performance.

5.2 Model II: Endogenous trip-chaining, activity space, transit demand, and residential location

In this extension, we relax the assumption of exogenous residential location. Given density, the model jointly determines the trip chain, the activity space, transit demand, and residential location. The equations of Model II are estimated by three-stage least squares (3SLS). All four equations pass the rank condition for identification. Equation (1) is overidentified, and Equations (2), (3), and (4) are just identified. The results are given in Table 4.

Table 5 reports selected point elasticities for statistically significant estimates. Compared to Model I, endogenous residential location reduces the magnitude of the elasticity of travel demand with respect to density by 19 percent. When households can locate anywhere in an urban area and when they adjust trip-chaining and commuting costs, an exogenous 20-percent increase in density produces a 1.4-percent increase in the demand for transit.

Accounting for self-sorting, through choice of residential location, reduces the relevance of transit-station proximity to the residence, indicated by an 35-percent decrease in magnitude in the point elasticity estimate with respect to Model I. An increase from 0.3 to 0.6 miles to the nearest transit station reduces transit demand by only 5.1 percent, as opposed to the 7.9-percent reduction of Model I. This result shows that self-sorting is less relevant than Cervero (2007) noted. He found that self-sorting accounts for about 40 percent of transit ridership for individuals residing near a transit station.

Table 4

Regression Results for Model II

Equation	*Coefficient*	*p-value*
(1) Trip-chaining, TC		
AS	0.0725	0.7140
RL	0.0096	0.4130
walk_dist	–0.0573	0.0000
veh	–0.0786	0.0130
act_tt	0.0014	0.0020
act_dur	–0.0022	0.0000
subc_dist	0.0435	0.0000
sch	0.0778	0.0000
constant	1.2604	0.0000
(2) Activity space, AS		
TC	0.2357	0.0000
D	–0.0858	0.0000
act_dur	–0.0007	0.0000
hhinc	0.0412	0.0000
r_est	–0.0014	0.0000
constant	2.0943	0.0000
(3) Transit demand, TD		
TC	–0.6964	0.0000
AS	–0.2598	0.0250
RL	–0.0090	0.3110
walk_dist	–0.0669	0.0000
tswork	0.3716	0.0000
prkride	–0.0669	0.2020
ts_tod	0.1304	0.2560
veh	–0.0365	0.0990
constant	–0.1119	0.2720
(4) Residential location, RL		
TC	3.7324	0.0000
TD	–1.2408	0.0080
hprice	–2.8117	0.0000
hage	–0.0849	0.0000
rooms	1.1279	0.0000
div	–2.6312	0.0000
pov	–5.9629	0.0130
own	0.4966	0.0620
constant	39.1808	0.0000

$N = 8{,}212$; $F_{TC}=42.7$; $F_{AS}=72.5$; $F_{TD}=118.5$; $F_{RL}=57.2$

Table 5

Selected Elasticities from Model II

Elasticity	*D*	*walk_dist*	*subc_dist*	*r_est*	*tswork**
TC	–0.006	–0.052	0.115	–0.002	–
AS	–0.087	–0.014	0.032	–0.033	–
TD	0.072	–0.051	–0.277	0.028	0.372
RL	–0.006	–0.002	0.060	–0.002	–

*Indicates a proportional change.

The specification of Model II helps us understand the reasons for the changes from Model I. In Model II households optimally choose residential location and non-work activities, choices that optimally define the spatial extent of non-work activities. Households locate their residences farther from their job locations, trading lower housing costs for increased commute distance. Trip-chaining optimization is part of this tradeoff, which leads to an expansion of the activity space. This, in turn, reduces opportunities to use transit for non-work travel. This behavior is empirically validated by the statistical significance of all housing and neighborhood controls in the residential location equation.

5.3. Model III: Endogenous trip-chaining, activity space, transit demand, residential location, and density

In this extension, we relax the assumption of exogenous density. The model jointly determines the trip chain, the activity space, transit demand, residential location, and density. The equations of Model III are estimated by three-stage least squares (3SLS). All five equations pass the rank condition for identification. Equation (1) is overidentified, and the other equations are just identified. The results are given in Table 6.

Table 6

Regression Results for Model III

Equation	*Coefficient*	*p-value*
(1) Trip-chaining, TC		
AS	1.00867	0.0000
RL	0.07774	0.0000
walk_dist	–0.66261	0.0000
veh	–0.02917	0.3570
act_tt	–0.00093	0.0560
act_dur	–0.00036	0.2650
subc_dist	0.18745	0.0000
sch	0.05695	0.0000
constant	–2.93691	0.0000
(2) Activity space, AS		
TC	0.53891	0.0000
D	–0.28170	0.0000
act_dur	–0.00004	0.8390
hhinc	0.01819	0.0000
r_est	–0.00177	0.0790
constant	3.51093	0.0000
(3) Transit demand, TD		
TC	–0.23095	0.0030
AS	0.21302	0.0540
RL	0.01619	0.0700
walk_dist	–0.47395	0.0000
tswork	0.44630	0.0000
prkride	–0.07878	0.0840
ts_tod	0.12797	0.1980
veh	–0.06411	0.0020
constant	–1.31138	0.0000
(4) Residential location, RL		
TC	2.46949	0.0000
TD	–1.16775	0.0130
hprice	–2.79304	0.0000
hage	–0.09605	0.0000
rooms	1.34316	0.0000
div	–6.19042	0.0000
pov	–4.50750	0.0060
own	1.37799	0.0000
constant	40.31047	0.0000
(5) Density, D		
RL	–0.00907	0.4000
AS	–0.53331	0.0000
cbd_dist	–0.04010	0.0000
subc_dist	–0.07071	0.0190
constant	11.76875	0.0000

N= 8,212; χ^2_{TC}*=2,512.8;* χ^2_{AS}*=611.2;* χ^2_{TD}*=1,712.7;* χ^2_{RL}*=646.3;* χ^2_{D}*=1,448.6*

In the long run, the simultaneous choice of location and travel affects urban density. Aspects of this relationship have been considered in the literature. For example, while modeling long-run transit demand responses to fare changes, Voith (1997) treats density as endogenous and as being affected directly by transit patronage levels. In the long run, these levels are affected by supply-side changes. Voith (1997) assumes that as transit services improve, more people live in proximity to transit stations, thus increasing the demand for transit services.

Our estimation shows that both CBD and subcenter distance from the residence are statistically significant in determining density. The signs of *cbd_dist* and *subc_dist* are negative, as expected. This finding indicates the strong spatial attraction of the CBD relative to subcenters even within a polycentric urban area, such as the San Francisco Bay area.

The relevance of these two variables is highlighted by the elasticities in Table 7, which compares the point elasticities of Model III with preceding estimates. The elasticity of travel demand with respect to walking distance is greater in absolute value than those of Model I and Model II. An increase from 0.3 to 0.6 miles to the nearest transit station reduces transit demand by 76.9 percent, compared to the 7.9-percent reduction of Model I and the 5.1-percent reduction of Model II. The presence of a transit stop at the workplace increases the demand for transit by 44.6 percent, increasing the importance of that variable in this model as compared to the others.

Treating density endogenously results in a more elastic travel demand with respect to distance to the nearest transit center. The elasticity of transit demand with respect to distance to the CBD (–0.09) is substantially less in absolute value than the elasticity with respect to distance to the nearest subcenter (–0.45). In other words, transit patronage is more responsive to a residential location near a subcenter than near the CBD. This result is consistent with recent findings of increased transit use in better served decentralized urban areas (Brown and Thompson, 2008;

Thompson and Brown, 2006) and findings showing that transit ridership is not affected by the CBD (Brown and Nego, 2007).

Table 7

Selected Transit-Demand Elasticities[6]

Elasticity	*Model I*[a]	*Model II*[b]	*Model III*[c]
Density	0.089	0.072	*na*
Walking distance	–0.079	–0.051	–0.769
*Transit station at workplace**	0.385	0.372	0.446
*TOD station**	0.206	*na*	*na*
Distance to CBD	*na*	*na*	–0.087
Distance to nearest subcenter	–0.282	–0.277	–0.385
Retail establishments density	0.045	0.028	0.077
Residential location	–0.097	*na*	*na*

[a]Residential location and density exogenous.
[b]Density exogenous. [c]All endogenous. *na* = not available.
*Indicates a proportional change.

6.0 Summary of Findings

There is a lack of empirical work examining the relationship between urban form and travel behavior that accounts for trip-chaining, among other travel complexities. To fill this gap in the literature, we developed and estimated three simultaneous-equation models of transit usage and urban form.

Our models allow household travel to respond to changes in urban form by considering trip-chaining for non-work travel. In the models, trip-chaining results from households' reductions in non-work travel time, while accounting for constraints imposed by the built environ-

[6]The variables *cbd_dist*, *subc_dist*, and *r_est* appear as explanatory variables but are treated as endogenous in the model. An initial specification treated these three variables as exogenous, but overidentification tests show that this treatment led to weak instruments, a problem leading to inconsistent estimates. McMillen (2001) finds that subcenters are endogenous to density.

ment. Travel-time saving is spent on additional non-work travel or provides inducement to reassess residential location decisions. These changes in travel behavior and residential location then affect the demand for travel.

The constraints imposed by the built environment are captured by the activity space. Empirical evidence shows that lower densities define a larger activity space, which, in turn, decreases transit use. Conversely, as density increases, the activity space contracts, as does the need to engage in complex trip chains.

Idiosyncratic preferences for transit also affect transit demand. For example, in the absence of adequate transit, households engaging in complex trip chains, independent of changes in the surrounding built-environment, may use the automobile. In contrast, if adequate transit services are available, households would choose transit, other things equal.

Exogenous density change does not have a large effect on transit demand, and the magnitude of the effect decreases when residential location becomes endogenous. A 20-percent increase in gross population density (1,830 persons per square mile) increases transit demand from a minimum of 1.4 percent to a maximum of 1.8 percent.

The importance of station proximity to transit demand decreases after accounting for idiosyncratic preferences for location. In Model II, the elasticity of transit demand with respect to walking distance is about one-third smaller than in Model I, in which residential location and density are exogenous. This decline in magnitude results from allowing households to choose their residential location and by accounting for omitted-variable bias. On the other hand, the endogenous treatment of density and station proximity results in a much higher elasticity (–0.77).

Transit station proximity to a workplace also has a significant positive impact on ridership, as indicated by the magnitude of the proportional changes across all three models. Likewise, in Model I transit-oriented development near transit stations has a positive impact on transit use; a TOD stop increases transit demand by about 21 percent. A transit station near a workplace exerts a positive impact on ridership, as indicated by the magnitude of the proportional changes across all three models.

The CBD is not an important driver of transit use, as highlighted by an elasticity of transit demand with respect to distance to the CBD of –0.09. Subcenters play a more important role, and our findings support a policy of providing transit services in decentralized employment and residential areas to increase ridership.

The importance of mixed-use development to increase transit patronage is highlighted by the elasticity of travel demand with respect to retail establishment density. Model II shows that a 20-percent increase in retail establishment density (or about 28 establishments per square mile) increases transit demand by 1.5 percent.

Households living farther from work use less transit, which is due to trip-chaining behavior. Such households engage in complex trip chains and have, on average, a more dispersed activity space, which requires reliance on more flexible modes of transportation. The results support policies that would reduce the spatial allocation of activities and improve transit accessibility at and around subcenters. Similar results can be obtained by policies that increase the presence of retail locations in proximity to transit-oriented households.

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