Decentralization of Jobs and Emerging Suburban Commute

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Large-scale suburbanization of employment has dramatically changed transportation and land use planning. Intersuburban commuting now dominates regional highway networks, and the automobile has replaced mass transit for many commutes. A study was undertaken to examine one aspect of the debate on the effects of employment decentralization on regional mobility: the impact of growing suburban employment on the commutes of people from various income groups. The study suggests that suburban employment centers with high levels of multifamily housing will exhibit commute patterns in which household income and commute distance are largely independent. In contrast, in suburban areas in which the development of dense housing has not kept pace with employment growth, it is hypothesized that new commute patterns are emerging wherein lower-income households commute greater distances than their upper-income counterparts. This pattern would reverse the prediction of monocentric urban models for central city employment. These hypotheses are tested for San Francisco Bay Area communities using data from 1981 and 1989. Bivariate analyses generally supported the predicted effects of community employment base and housing stock on commute patterns by income. Nested logit models of the household residential location decision were estimated for workers in San Ramon and in northern Santa Clara County on the basis of 1989 data. The models appeared to demonstrate a positive effect of the availability of multifamily housing on the residential location decisions of low- to moderate-income households. Forecasts of commute patterns using the estimated models indicated a potential for reducing long-distance commutes by low- to moderate-income households through a policy encouraging multifamily housing construction in the vicinity of suburban employment centers.

Rapid employment growth in many suburban areas during the 1980s markedly affected the range of available transportation planning strategies. Suburb-to-suburb commutes currently outstrip both intraurban and suburb–to–central city journeys to work; nationwide, a plurality of metropolitan commutes now begin and end outside central cities (*1*). Transit's mode share declines sharply with employment suburbanization because suburban employment locales are virtually impossible to serve by conventional transit because of scattered trip ends (*1–3*). Even ride sharing may become more difficult when increasing numbers of people work in sites with fewer nearby workers than in more traditional downtown employment settings.

Trends toward intersuburban commuting and greater reliance on the private automobile associated with employment suburbanization are not in great dispute. Much more controversial are the implications of these trends for transportation and land use planning as well as for the prospects for metropolitan areas in general. One point of view is that large-scale employment suburbanization harms the long-term viability of metropolitan areas by reinforcing automobile dependency and promoting environmental destruction through excess land consumption and air pollution (*4*). An alternative viewpoint is that decentralization is the force that renders accessible large metropolitan areas. By eliminating the need to commute from the metropolitan periphery to the central business district (CBD), employment suburbanization has kept commute distances in larger urban areas from growing to unmanageable proportions (*5*).

A third view accepts the inevitability of large-scale employment suburbanization but points to a systematic separation between suburban workplaces and suburban residences as a continuing impediment to regional mobility (*6–8*). Despite the traditional conception of the "suburb," some suburban communities have a large employment base relative to a limited housing stock, whereas others contain the reverse. Intersuburban commuting, now the dominant form of metropolitan journeys to work, is the result. The "jobs-housing balance" approach seeks to identify those economic and political forces that lead to deficits of housing near suburban employment centers, and to develop structures for planning and development that would generate a better geographic match between employment and housing. The geographic matching would presumably obviate the need for much of the intersuburban commuting that has been observed recently.

Separation of jobs and housing is a product of affordability and not merely space; imbalances between jobs and housing are most important for those households unable to afford scarce housing near suburban employment centers. The effects of employment suburbanization are thus best analyzed with specific reference to the various income groups affected. This study examines one aspect of the debate on the effects of employment suburbanization on regional mobility: the impact of growing suburban employment on the commutes of people from various income groups. The study poses three major questions: (a) Does suburban employment tend to favor the commutes of one income group or another? (b) If income-related commute patterns are evident among commuters to suburban employment centers, is there a relationship between observed commute patterns and characteristics of the particular suburban employment center being analyzed? and (c) Can policies allowing or encouraging development of higher-density housing near suburban employment centers reduce long-distance commutes by low- to moderate-income commuters?

These questions are analyzed with reference to the San Francisco Bay Area. Regional commuting characteristics are

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first explored through a descriptive analysis of the Bay Area Travel Survey (BATS), a 1981 home interview survey of some 7,200 households (*9*). The effects of local conditions on commute patterns are then analyzed through the estimation of a discrete choice model of residential location based on a 1989 workplace survey of workers at selected large employers in northern Santa Clara County, the region's high-technology manufacturing center, and in San Ramon, a suburb on the Bay Area's eastern edge that expanded rapidly in office employment over the 1980s.

The 1989 survey was administered by mail and distributed to samples of employees of selected large firms in San Ramon, Mountain View, Sunnyvale, Cupertino, and San Jose. The overall response rate was 56.2 percent. Survey respondents were significantly wealthier than the population at large; the mean household income of survey respondents ranged from 90 to 200 percent of the population mean household income for their communities of residence (median = 130 percent). Because of income biases in the sample, caution must be used in interpreting results.

MODELS OF URBAN DECENTRALIZATION

The analysis of income-related patterns in metropolitan commutes was a central topic in much location theory of the 1960s and beyond (*10–12*), a literature that has been ably reviewed elsewhere (*13–17*). Under the standard assumptions of employment locating at the center of the metropolitan area, and an income elasticity of demand for residential space exceeding the income elasticity of commute costs, the prediction of this "monocentric" theory was a pattern of concentric rings of residential zones of increasing income radiating from the metropolitan center. Higher income was thus associated with longer journeys to work.

Later models analyzed decentralized or polycentric regions but diverged in their style of analysis. To a great extent this lack of a unified approach is attributable to the intractability of polycentricity (*17*). Some authors continued to derive monocentric models (*18–20*), whereas others restricted their prototypical urban area to one dimension (*17,21*) or allowed for only two centers (*22*). Researchers in the spatial interaction tradition focused on interzonal travel flows or systemwide transportation and location optima (*23,24*). With the exception of White (*25*), most nonmonocentric modelers did not deal explicitly with the question of spatial distribution of residences by income, a feature that was so prevalent in their monocentric precursors.

Another tradition of locational analysis emphasizes neighborhood characteristics and service differentials (over the commute distance–land price tradeoff) as determinants of residential location (*26–28*). This approach derives support from surveys in which households consistently rank factors such as quality of schools and safety and general appearance of neighborhoods as more important than workplace accessibility in determining their choice of residential location (*29,30*). This style of analysis is well suited to the description of dispersed urban areas because it refrains from making assumptions on the commute in the first place. But for most workers the commute remains a determinant of residential location, at least on a macro scale, and is logically a component of residential location analysis.

It has been suggested that urban decentralization models need to fuse the tradition of Alonso (*10*), which emphasizes elasticities of commute cost and space, with that of Tiebout (*26*), which emphasizes local service differentials (*13,31*). This is a realm in which the discrete choice family of models can excel and perhaps provide an empirical bridge between these two theoretical approaches. This is a result of the ability of discrete choice location models to analyze jointly two sets of characteristics: (a) attributes of potential residential locations such as public service levels; and (b) attributes arising from the interaction of individual households and communities, such as housing affordability or commute distance. This capacity represents a crucial difference between the discrete choice approach and the family of regression-based tools that tend to focus on the household or the community but rarely on both simultaneously.

For problems with more than one possible outcome (e.g., the selection of a single community from many possible communities), the most commonly applied discrete choice technique is the multinomial logit model. Following the notation of Ben-Akiva and Lerman (*32*), the multinomial logit model assumes that the probability that the utility of community i exceeds the utilities of all other communities j for household n (i.e., the probability that i is the chosen alternative) equals

$$P_n(i) = \frac{e^{Vin}}{\sum_{j \in Cn} e^{Vjn}}$$

where V is the deterministic component of a choice's utility and is a function of the attributes of the communities (e.g., school quality, tax rate) and attributes arising from the interaction of households and communities (e.g., income-housing price ratio, commute distance), and C_n is the set of communities available to the household or the "choice set."

The first major application of the discrete choice approach to locational modeling was Lerman's model of household locational choice between 145 census tracts in Washington, D.C. (*33*). In assuming a joint selection among so many alternatives, the pioneering work demonstrated the feasibility of a multinomial logit model of residential location but also showed the need for alternative representations of choice to comply with the "independence from irrelevant alternatives" (IIA) limitation of the multinomial logit model. To overcome this limitation, later models employed a hierarchical modeling structure (the nested logit model) in which secondary choices are modeled as conditional on primary-level choices. These hierarchical models have taken various forms, such as a locational decision conditional on a decision to move or to stay in place (*34*), or mode to work conditional on vehicle ownership, which in turn was conditional on residential location (*35,36*). Quigley modeled the choice of housing unit conditional on neighborhood selection, which was modeled conditionally on choice of town (*37*). In each of these cases, the utility of a location to an individual was modeled as a function both of attributes of the location and an interaction of locational and household characteristics.

Anas developed a model of the Chicago area rental market that differed from those referred to above in two important ways (*14*). First, the model used U.S. census data aggregated into 0.25-mi^2 zones over the Chicago metropolitan area rather than the disaggregate household level data used in other studies. The second difference of Anas's work is its analysis of both the demand and supply sides of the rental housing market. Using a utility-maximizing model for households and a profit-maximizing model for landlords, Anas derived a partial equilibrium model of the housing market, an accomplishment that previously had been the domain of primarily bid rent analyses.

COMMUTE PATTERNS IN BAY AREA SUBURBS

The view associating large-scale employment suburbanization with enhanced overall regional mobility is largely based on two premises. First, it is assumes that commutes to suburban locations are shorter in distance than those ending at the metropolitan center. The second premise is that employment suburbanization benefits different income classes equally, or that the ability of a household to reside close to its suburban workplace is largely unaffected by its income status.

Shortened Commutes in Suburbs?

The first premise, that of shortened commutes in the suburbs, is generally supported by the 1981 BATS data. Figure 1 presents median commute distances by superdistrict (34 aggregations of travel analysis zones encompassing the entire Bay Area). As expected, the longest commutes end in downtown San Francisco, with a median distance of 19.3 mi. The San Francisco CBD's position at the tip of a peninsula lengthens commutes significantly; the commutes of the Oakland workers represent more typical center city commutes, with a median distance of 12.2 mi.

Workers in suburban areas tend to enjoy shorter commutes; median trip distances are less than 8 mi in most areas. The commute benefits of suburbanization are not universal, however. Commutes of near–center city length are found among workers in the industrial suburbs of northern San Mateo County (12.1 mi) and Richmond (9.5 mi). Both areas contain concentrations of heavy industry and populations of low or lower-than-average incomes and may be viewed as being similar to center cities in their commute patterns. In contrast, the longer commutes among workers employed in northern Santa Clara County, the heart of the Silicon Valley high-technology manufacturing region (medium = 8 mi), occur against a backdrop of relatively cleaner electronics manufacturing and a higher-income population. It may be that the long median commute in this area is affected by the acute surplus of jobs over housing in the area and the necessity for much in-commuting (7).

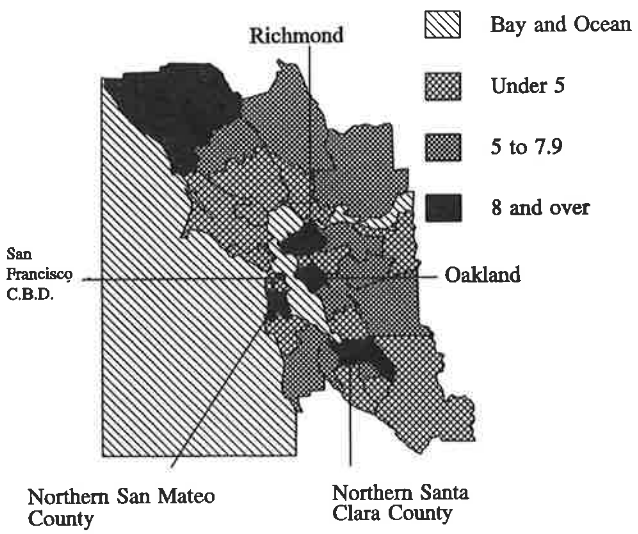

FIGURE 1 Median commute distance (mi) by superdistrict of employment, 1981.

Suburban Employment and Commutes by Income

The prediction of the monocentric model of increasing incomes of central city commuters with increasing commute distance is supported by the 1981 BATS data. Figure 2 maps the Pearson correlations (r) between household income and commute distances for primary workers employed in each of the Bay Area's 34 superdistricts. Although the magnitude of the correlations indicates that income has little explanatory power in predicting commute distances, the correlation between commute and income is positive as expected for the downtown areas of San Francisco (r = .28) and San Jose (r = .21) and for the city of Oakland (r = .08). The low correlations indicate that there remains a great deal of unexplained variation of income over the entire commuting range, not a surprising result given the great variety of settlement patterns in the cities as well as in the suburbs.

Although the three central cities all exhibit the expected positive correlation between commute distance and income, the pattern of relationships between income and commute varies more widely in suburban and exurban areas. Positive correlations appear in the fringes of the metropolitan area, such as eastern Alameda County (r = .35), eastern Solano County (r = .22), and the Santa Rosa area (r = .20), as well as in some of the industrial suburbs: Richmond (r = .27), northern San Mateo County (r = .25), and northern Santa Clara County (r = .09).

Within the Bay Area's inner ring, most suburban superdistricts exhibited independence between household incomes and commute distances in 1981. Exceptions to this were found in the same areas that exhibited longer-than-typical suburban

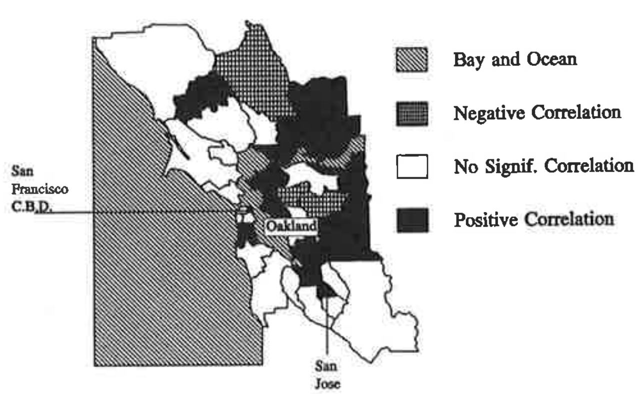

FIGURE 2 Correlations between household income and primary worker's commute distance, by superdistrict of employment, 1981.

commutes and thus may be somewhat "urban" in their commute characteristics: Richmond area (r = .27), northern San Mateo County (r = .25), and northern Santa Clara County (r = .09). Data from 1989 revealed no significant relationship between incomes and commutes for northern Santa Clara County.

In contrast, in two of the Bay Area's suburban superdistricts, higher-income workers lived closer to their workplaces than did those from lower-income households. These areas included the Interstate 680 corridor communities of Walnut Creek and Lafayette (r = −0.18) and Danville and San Ramon (r = −0.29).

Despite incompatibilities of data sources, 1989 and 1981 survey data revealed similar patterns; the correlation between income and commute distance remained negative and significant for the San Ramon workers, although once again without much explanatory power (r = −0.11) because of a high variance of commute distance at all income levels. Despite the low explanatory power of income on commute distance, a commute distribution histogram (Figure 3) reveals a clear pattern of commute distances by income; among the highest-earning households, 26.9 percent lived within 4 mi of their San Ramon workplace, whereas only 16.5 percent of those households earning up to $50,000 lived within so close a commuting range. The opposite pattern emerges when one considers the longest commute of 40 mi or more.

Thus the hypothesis of an income-neutral effect of employment suburbanization appears to hold in some areas and not in others. Given intersuburban differences, blanket statements about the effect of employment suburbanization on metropolitan commutes may be misleading. Instead, a finer-grained approach relating local conditions to the commute patterns to which they give rise may be more instructive from both a theoretical and policy standpoint. In particular, it may be that the effect of suburban employment on the commutes of people from different income groups is largely a product of local housing stock conditions. Initial analysis of housing stock conditions in the San Ramon area and in northern Santa Clara County are revealing; Silicon Valley communities have a significantly higher proportion of their housing stock in multifamily units (between 41 and 72 percent, compared with 27 percent for San Ramon). It is hypothesized that differences in the income-commute relationship between the two areas (negative for San Ramon and insignificant or positive for northern Santa Clara County) are in part a product of these differences in housing stock conditions.

MODELING APPROACH

Commute patterns are primarily the result of locational decisions by households and employers. This study models household locational decisions given employment at a fixed workplace or two fixed workplaces in the case of the dual-worker household.

Choice Set Development

The capacity of the multinomial logit model to analyze both characteristics of the individual and the community requires an explicit delineation of the set of communities from which the individual chooses. The feasible set of communities for all households in the sample—the choice set—was assumed to be those communities within a 60-min driving radius of the workplace, generating choice sets of 69 communities for the San Ramon employees and 52 communities for the northern Santa Clara County employees. The massive data sets generated by the large numbers of alternatives in the choice sets were reduced through a random sampling procedure proposed by McFadden (*38*).

Modeling a household's locational choice between such a large number of communities would strain the behavioral interpretation of the model; selection of one of 69 commu-

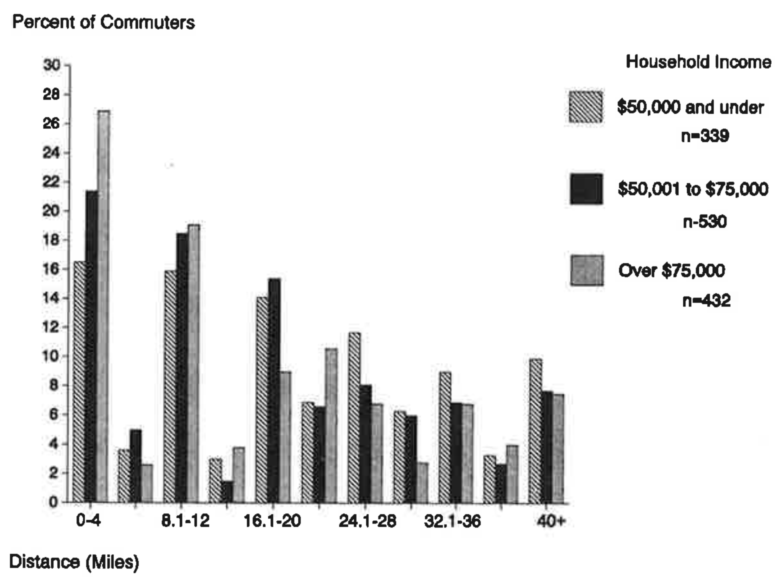

FIGURE 3 Commute distance distribution by household income group, San Ramon workers, 1989.

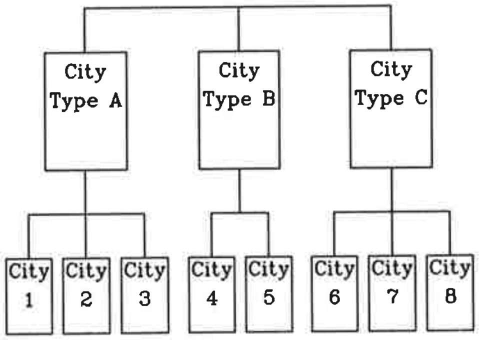

FIGURE 4 Diagram of nested structure of communities within community clusters.

TABLE 1 Grouping of Communities for Nested Analysis, Choice Set for San Ramon Workers

Median Single Family Home Price	Percent of Housing Stock in Multifamily: 33 percent and under	Over 33 percent
$227000 and under	Antioch Benecia Brentwood El Sobrante Livermore Manteca Martinez Newark Oakley Petaluma Pinole Pittsburg San Lorenzo Suisun Tracy Vacaville Vallejo	Concord Fairfield Hayward Pleasant Hill Richmond San Leandro San Pablo SJ: Alum Rock SJ: Downtown Union City
$227,001-$307,000	Castro Valley Dublin El Cerrito Fremont Half Moon Bay Kensington Milpitas Pleasanton San Ramon SJ: Berryessa SJ: Cambrian/Blsm Hill SJ: Zipcode 95125	Alameda Albany Berkeley Campbell Colma Daly City Hercules Oakland Santa Clara SJ: Evergreen S San Francisco Walnut Creek
Over $307,000	Alamo Danville Lafayette Los Altos Orinda Piedmont San Carlos Saratoga	Belmont Cupertino Foster City Los Gatos Moraga Mountain View San Francisco San Mateo SJ: Westgate Sunnyvale

(SJ: City of San Jose)

nities is beyond the cognitive skills of most households. Moreover, modeling the locational decision in such a matter would undoubtedly violate the IIA limitation of multinomial logit. For these reasons, selection of community was modeled as conditioned on a prior selection of a generalized community type, or cluster (Figure 4). Clusters of communities were developed on the basis of housing price (i.e., three levels of median single-family housing prices) and density (i.e., two levels of multifamily housing stock) as described in Table 1. These dimensions were used on the assumption that price and density form the primary components of housing affordability; communities within a cluster should thus have similar affordability characteristics. As discussed later, results of the analysis confirm the appropriateness of this as a valid nested framework for modeling residential location decisions.

Modeling Results

Variables used in the analysis are described in Table 2; the choice modeled was residence in one of 69 communities. The models in Table 3 are designed to assess the impact of multifamily housing on the utility of a particular community to low- and moderate-income households. Independent variables include those pertaining to access, affordability, and community attributes. Some variables vary by community (SCHOOL, CRIME, CENTERDUMMY), others vary by household and by community (the commute time variables HTIME and LTIME, the affordability variables $SQFT/INC, %MULT:LO, %MULT:MED, and %MULT:HI, as well as TENURE/$ and MFCHILD), and others vary by household and by community cluster (MED$/INC, LOGSUM).

On basis of these categories of variables, the total utility to a household of a particular community and community cluster together is equal to

$$U_{imn} = \bar{V}_i + \bar{V}_{in} + \bar{V}_{mn} + \bar{\varepsilon}_i + \bar{\varepsilon}_{in} + \bar{\varepsilon}_{mn}$$

where

- U_{imn} = total utility of community i and community cluster m to household n;
- $\bar{V}_i$ = systematic component of utility common to all elements of C_n, using community i (the "¯" refers to a subset of the entire choice set C_n);
- $\bar{V}_{in}$ = remaining systematic component of utility specific to combination (i,n);
- $\bar{V}_{mn}$ = remaining systematic component of utility specific to combination (m,n);
- $\bar{\varepsilon}_i$ = unobserved components of total utility attributable to community choice;
- $\bar{\varepsilon}_{in}$ = unobserved components of total utility attributable to interaction of households and community choice; and
- $\bar{\varepsilon}_{mn}$ = unobserved components of total utility attributable to interaction of households and community cluster.

Three models were estimated for San Ramon employees and three for workers in northern Santa Clara County. Nested logit models were estimated using the LIMDEP statistical package compiled on the Berkeley Cray X-MP/14 under un-

TABLE 2 Variables Used in Multinomial Logit Models

Access Variables

HTIME: Peak hour automobile travel time from accepted or rejected place of residence to place of work of the highest wage earner in the household.

LTIME: Peak hour automobile travel time from accepted or rejected place of residence to place of work of the second wage earner in the household.

Affordability Variables

$SQFT/INC: Median 1989 price per square foot of single family homes in a community divided by total annual household salary (in thousands).

$MED/INC: Median home price for all communities (within a cluster of communities) divided by household income.

%MULT: Proportion of housing stock in a community in non-single family homes. This includes duplexes, apartment, condominiums and mobile homes. This variable was partitioned into three according to household income level: %MULT:LO equals %MULT for households with incomes of up to $50,000 and 0 otherwise; %MULT:MED was constructed similarly for households of incomes between $50,000 and $74,999; and %MULT:HI for households of incomes of $75,000 and above. Each of these variables was designed to measure the utility of multifamily housing in a community to households of a different income stratum.

TENURE/$: For homeowners, equal to the number of years of residence at their current address divided by community median home price. The variable is equal to 0 for renters. This variable is designed to capture the effect of an inflating housing market; long term owners may tend to live in higher priced communities than newcomers.

Community Service and Amenity Variables

SCHOOL: Aggregated test results from California Assessment Program standardized testing for 1989. SCHOOL was the median of six scores: statewide percentile rankings for third, eighth and twelfth grades in reading and mathematics.

CRIME: Residential and commercial burglaries per capita, 1989.

MFCHILD: Equal to %MULT for households with children present, 0 for other households. This variable is designed to measure any disutility of multifamily housing in a community to household with children.

Centerdummy: A center-city dummy variable, equalling 1 for residence in San Francisco and Oakland and 0 for all other cases.

Variable Used in the Estimation of Nested Logit

LOGSUM: A variable used in the nested logit model (also referred to as the inclusive value, or I), equivalent to the expected utility of the community level nest:

$$I_{mn} = \ln \sum_{i \in D_m} e^{(V_i + V_{in})}$$

where D_m is cluster of communities m available to household n (i.e., a subset of the full choice set C_n). The coefficient of this variable, μ, becomes an indicator of the appropriateness of the hierarchical structure assumed, with values of μ greater than 0 and less than 1 validating the postulated relationship.

The probability of a household n choosing community cluster m and community i becomes:

$$P_n(i,m) = \frac{e^{(V_{mn} + \mu I_{mn})}}{\sum_{m \in D_m} e^{(V_{mn} + \mu I_{mn})}} \; \frac{e^{(V_{in} + V_i)}}{\sum_{i \in C_n} e^{(V_{in} + V_i)}}$$

constrained maximum likelihood sequential estimation. The starting point for the modeling is the place of work; thus the "San Ramon model" refers not to a model of San Ramon residents but to San Ramon workers who may live virtually anywhere in the Bay Area and beyond. In each case, Model 1 represents a model using the full set of variables; Model 2 drops insignificant variables, as well as LTIME, the commute time of the secondary earner in the household. This accounts for the possibility that residential location decisions may be made with reference to a primary worker's place of employment, with a secondary worker seeking employment close to home (i.e., opposite direction of causation). The preferred models restore the LTIME variable, as well as significant variables from Models 1 and 2.

Model Evaluation and Interpretation

The initial hypothesis of a nested structure with community clusters forming the higher-level nest and individual communities forming the lower level was validated by modeling results. The coefficients of the LOGSUM variable (μ) were statistically discernable from unity in both cases. Thus joint

TABLE 3 Alternative Nested Logit Model Specifications

	San Ramon			Santa Clara		
Variable	Model 1	Model 2	Preferred Model	Model 1	Model 2	Preferred Model
Lower level nest (community choice) variables (t-statistics)						
HTIME	-0.0672	-0.0754	-.0677	-0.0687	-0.0725	-0.0680
	(-13.8)	(-17.0)	(-14.3)	(-12.5)	(-14.3)	(-12.71)
LTIME	-0.06310		-.0618	-0.0497		-0.0494
	(-13.3)		(-13.4)	(-7.95)		(-8.07)
$SQFT/INC	-0.6847	-0.524	-.6513	-0.5073	-.5605	-.5399
	(-5.68)	(-5.1)	(-5.86)	(-2.88)	(-3.59)	(-3.34)
%MULT:LO	3.38540	2.9235	3.4334	4.2524		4.4481
	(3.230)	(2.93)	(3.37)	(2.089)		(2.234)
%MULT:MED	not estimable			-0.6612		
				(-0.46)		
%MULT:HI	2.0393			-0.5383		
	(1.80)			(-0.39)		
Centerdummy	2.0813	2.1344	2.0287	3.7664	4.1276	3.6321
	(7.31)	(8.55)	(7.46)	(5.623)	(8.07)	(6.52)
SCHOOL	0.0102	0.0100	0.0122	0.02547	0.0266	0.0256
	(2.34)	(2.71)	(3.05)	(4.255)	(4.69)	(4.312)
MFCHILD	0.5729			-4.5821	-4.941	-4.981
	(0.44)			(-2.70)	(-3.7)	(-3.41)
TENURE/$	-0.253			2.5153		
	(-0.3)			(0.528)		
CRIME	-13.73			-1.069		
	(-1.2)			(-0.05)		
Model statistics: Lower level nest						
L*(0):	-1494.1	-1494.1	-1494.1	-570.6	-570.6	-570.6
L*(ß'):	-898.26	-1024.5	-901.96	-364.5	-406.6	-364.8
rho^2:	0.3988	0.3143	0.3963	0.3612	0.2874	0.3606
rho(bar)^2:	0.3914	0.3110	0.3923	0.3520	0.2787	0.3487
Upper level nest (choice of community clusters) variables						
$MED/INC	-0.100		-.1390	0.0840		
	(-3.9)		(5.39)	(3.13)		
LOGSUM	0.5988	0.8417	0.5979	0.3258	0.3398	0.3089
	(17.2)	(16.9)	11.65	(7.38)	(7.16)	(16.38)
(The t-statistics of the LOGSUM test H_o: $ß=1$ rather than H_o: $ß=0$.)						
Model Statistics: Upper level nest						
L*(0):	-1167.0	-1167.0	-1167.0	-536.0	-536.0	-536.0
L*(ß'):	-939.81	-965.98	-934.18	-495.3	-505.7	-504.4
rho^2:	0.1947	0.1723	0.1995	0.0759	0.0565	0.0589
rho(bar)^2:	0.1927	0.1714	0.1977	0.0722	0.0547	0.0570
Summary statistics for both levels						
L*(0):	-2661.1	-2661.1	-2661.1	-1106.6	-1106.6	-1106.6
L*(ß'):	-1838.1	-1990.5	-1836.1	-859.79	-912.3	-869.23
rho^2:	0.3093	0.2520	0.3100	0.2230	0.1756	0.2145
rho(bar)^2:	0.3044	0.2497	0.3071	0.2113	0.1702	0.2064
No. of Observ.	1,475	1,475	1,475	480	480	480

(i.e., non-nested) models of locational choice would have violated the crucial IIA assumption of the logit model and would thus have biased parameter estimates.

The coefficients of HTIME and LTIME are both negative and significant, indicating a disutility of commute time in community selection. It appears that although locational factors such as neighborhood amenity and school quality may rank uppermost in the locational considerations of households, the search for adequate environments is conditioned on the acceptability of the commute. The other half of the accessibility-price tradeoff is captured in $SQFT/INC, the median single-family price per square foot divided by income in thousands of dollars. The coefficient of this variable is negative and significant; controlling for commute distance and locational characteristics, households prefer housing that requires a lower proportional expenditure of income.

The statistical significance of LTIME, along with the fact that it perturbs neither the direction of HTIME nor its statistical significance, appears to indicate the importance of secondary workers' job locations as independent factors in households' residential decision making. Undoubtedly many decision-making patterns exist in households, including those that limit the location of the secondary worker's job according to a previously determined household location. But for a large number of dual-worker households, residential location seems to be determined with reference to both workplaces.

The positive coefficient of the CENTERDUMMY variable can be interpreted in two ways. First, it appears that center city living (i.e., in Oakland and San Francisco) on balance constitutes a draw given the variables measured here. A major part of the apparent attraction may be that the low standardized school test scores (SCHOOL) for Oakland and San Francisco are irrelevant to many of the well-paid workers in this survey because upper-middle-class members of these communities commonly send their children to private elementary and secondary schools. Another factor influencing CENTERDUMMY's significant positive coefficient is that the two San Ramon firms surveyed relocated to San Ramon from central locations in 1984. A number of people who still live close to their former workplaces in the central Bay Area may be unable or unwilling to move. Nonetheless, the effect of central city location remained positive in the Santa Clara County model, which did not include recently relocating firms.

The most important policy variable in the model is $MULT:LO, equal to percentage of a community's housing stock in multifamily housing for households with up to $50,000 income (and 0 otherwise). The significant and positive sign of $MULT:LO is interpreted as indicating the importance of multifamily housing in a suburban community to low- to moderate-income households. Although these results should be viewed with caution because of sample biases, the results appear to imply that when controlling for other factors, such as housing price and school quality, an increase in multifamily housing levels in a suburban community increases the likelihood of selection of that community by low- to moderate-income households. If the community is a job center, changes in the housing stock may also reduce commutes by these households. These effects are modeled in the next section.

Despite the apparent commute-reducing potential for such residential development, there are many sides to the jobs-housing balance complex. As evidenced by the negative utility of MFCHILD in the Santa Clara County model, increased residential densities can tend to repel households with children. Thus, a policy of increasing housing density may eventually suffer from decreasing or even negative marginal returns in its potential to reduce commuting. Replicating urban levels of multifamily housing in suburban employment centers may eventually incur the costs of central city–style development in congestion and in-commuting by larger households without the crucial transportation advantages of a central location. Results of this study are speculative in this regard because of income biases in the sample; further research on the potential deterrent effect of suburban density is needed. Yet the potential of denser development to repel some people from seeking lower-density environments may be mitigated by adequately planning and zoning multifamily housing. Such planning will ensure open space for residents, as well as privacy sufficient to afford them some of the amenities of the more remote single-family house they may now be foregoing.

CHANGES IN COMMUTES IN RESPONSE TO CHANGES IN HOUSING STOCK

One of the most important uses of the multinomial logit model in land use and transportation modeling is its potential as a forecasting tool. Using already-calibrated coefficients, attributes of the choice sets (or the households themselves) may be manipulated to predict roughly the range of potential land use and transportation system responses to policy stimuli. For the purposes of this analysis, travel times are assumed to remain unchanged even with changes in the housing stock; this factor is clearly a simplification because a densifying housing stock near suburban employment centers would surely create some localized congestion even if it were to reduce long-distance commuting. Single-family housing prices are similarly assumed to remain unchanged by policy changes.

Two such housing policy options are tested for San Ramon. The first raises the levels of multifamily housing in San Ramon and neighboring Dublin by 10 percentage points, to the point that multifamily housing represents 36.7 and 38.6 percent of the housing stock, respectively (no addition to the single-family housing stock is assumed). This is equivalent to adding 1,815 multifamily units in San Ramon and 1,095 units in Dublin, on the basis of California Department of Finance figures (*39*). The model is then used to explore the question, Under these revised conditions, how many more households may be expected to locate in San Ramon or Dublin than would locate there under current conditions? What other communities would be expected to house fewer San Ramon workers if the San Ramon housing area stock were changed? The second policy experiment entails boosting the multifamily proportion of these communities' housing stocks to 50 percent, a figure typical of the communities studied in Santa Clara County.

Results of the simulation are presented in Table 4, which summarizes changes for all those communities forecast to gain or to lose San Ramon workers under the alternative housing stock scenarios described earlier. The first column represents the forecast when San Ramon's multifamily housing stock equals 36.7 percent and Dublin's equals 38.6 percent of the total. The values in Column 1 represent that percent of the sample forecast to live in that community that did not reside there before; thus 1.7 percent of the sample (over and above those currently living there) would be forecast to opt for living in San Ramon under the new housing stock conditions. Similarly, half of 1 percent of the sample of San Ramon workers is forecast to opt against living in Benecia in response to the housing stock change.

TABLE 4 Cities Forecast To Gain or Lose San Ramon Workers Under Increased Multifamily Housing Scenarios

City	Percent Change, add 10% Multifamily	Percent Change, 50% Multifamily	Auto Travel Time, Minutes	Travel Distance, Miles
San Ramon	1.70	3.08	4	2
Dublin	1.03	1.95	10	6
Hayward	-0.06	-0.06	30	12
Antioch	-0.07	-0.20	39	29
Pleasanton	-0.09	-0.08	14	10
Pittsburg	-0.13	-0.28	35	26
San Leandro	-0.13	-0.13	25	18
Martinez	-0.14	-0.28	33	21
Livermore	-0.14	-0.15	24	17
Concord	-0.20	-0.19	29	17
Pleasant Hill	-0.39	-0.86	20	13
Benecia	-0.50	-0.80	31	23
Walnut Creek	-0.90	-1.73	15	9

Column 2 represents the forecast locational response when both San Ramon and Dublin include 50 percent multifamily housing in their housing stock. Columns 3 and 4 represent approximate automobile travel time and travel distance from each community to San Ramon.

The expected result of this simulation was a diversion of commuters from affordable but remote communities. With the exception of Walnut Creek, all communities forecast to lose San Ramon workers are at least 10 mi removed from San Ramon, indicating a considerable potential for the reduction of commutes. Even the exception to this rule—Walnut Creek—presents an interesting case. Walnut Creek is 9 mi from San Ramon; it offers expensive housing (median single-family home price = $300,000) but a high proportion of multifamily housing as well; 59 percent of Walnut Creek's housing stock is in multifamily housing. Thus, despite its high cost of housing, it represents a relatively affordable community from which moderate-income households would be drawn if more affordable housing were to be constructed in San Ramon and Dublin. The result tends to confirm the jobs-housing balance approach to transportation planning that presumes that people would select housing that reduces their commutes if it were available at affordable prices. The findings presented above may underestimate for three reasons the commute-reducing potential of multifamily construction in these communities. First, as described, communities falling beyond a 60-min drive from San Ramon were excluded from the analysis so as not to perturb the results of the model with potential commutes that represented relevant options for only a tiny minority of San Ramon commuters. Commuters from these communities were excluded from the forecasting as well so as not to impute characteristics on untested data. An explicit forecast as to the behavior of these groups when faced with increased supplies of multifamily housing would require a housing type model to capture explicitly the tradeoff between affordable but dense housing nearby and larger, remote single-family homes. But to the extent that they come from moderate-income households, these long-distance commuters may be amenable to living in potential multifamily housing near their workplaces.

Second, the results presented below are for the household's primary worker only. Those multiworker households that would be most amenable to nearby higher-density living would be the ones for whom the move to Dublin or San Ramon reduces both commutes, not just one.

Finally, the models understate the commute-reducing potential of multifamily development because they include only those primary wage earners actually working in San Ramon. A new condominium unit in San Ramon occupied by, for example, a Dublin worker in all likelihood represents a shortened commute compared with commutes from alternative residential locations. The model simulates the behavior of San Ramon workers only and thus fails to capture these potential effects.

POLICY IMPLICATIONS

Cervero asserts that "[t]he principal reason for jobs-housing mismatches is that ad hoc market forces have generally shaped suburban growth in most U.S. metropolitan areas" (*7*). He hypothesizes five forces leading to the imbalance, two of which are demographic trends (two-wage-earner households and job turnover) and three of which are the product of planning and public decision making rather than the market: fiscal and exclusionary zoning, growth moratoria and worker earnings/housing cost mismatches generated by fiscal zoning and growth ceilings. The problem thus does not appear to be not enough planning; instead, it appears to be a planning style that seeks a localized kind of environmental quality (defined as large-lot, single-family development) without full regard for more regional concerns. The problem may in fact be too little rein given to the market rather than too much. General plans and zoning ordinances typically do not define minimum residential densities but rather maxima. The policy expressed in the San Ramon Housing Element of restricting high-density housing to just one of the city's eight planning subareas may be seen as one example of this phenomenon (*40*). It may be that allowing developers to build more densely near suburban job centers is all the incentive needed to produce significant residential densification near many suburban employment centers.

Results of this study are in accord with the jobs-housing balance approach to metropolitan transportation planning; when concentrations of suburban employment are matched with sufficient affordable housing, households seek to reduce commutes. Importantly, this approach is strictly a voluntary, incentive-based system; it is based on harnessing individuals' own desire to reduce commutes instead of imposing travel or mode restrictions that would be politically unpopular and intrusive on individuals' lives.

The commute-reducing potential of affordable housing depends on its occupancy by employees of nearby job sites. Results discussed above imply that San Ramon workers may actually occupy less than a quarter of new housing in the San Ramon vicinity. Policies to generate acceptance of nearby housing on the part of local workers can hold significant benefits in commute-reducing potential. When developers build housing in a community, they may be indifferent to its occupancy by local workers or by commuters. In contrast, to the extent that commute reduction is a public goal, it is in the community's interest that housing be occupied by local workers rather than out-commuters. It is not difficult to envisage community-developer agreements that would stipulate the nature and extent of locally targeted marketing for newly constructed housing to attempt to boost the proportion of housing occupied by local workers.

CONCLUSION

The conditions modeled in this study represent a single point in time, a snapshot in a continuum of development patterns that are constantly evolving. Many of those communities that appear to be lacking in alternatives to the single-family home today already have added considerable amounts of multifamily housing over the past decade and may in fact be on a path toward development patterns that will afford households the kind of choices referred to here.

The future course of these communities is still open. It is becoming increasingly clear that decision makers in suburban communities must recognize trade-offs between high employment levels, low-density residential environments, and uncongested highways; these three traditional goals may not be achievable simultaneously. When communities offer a range of dwelling and commuting choices, individuals and households will respond in ways that can meaningfully improve the quality of living in metropolitan areas.

ACKNOWLEDGMENTS

The author wishes to acknowledge the support of the University of California Transportation Center for this research. Many thanks also to Elizabeth Deakin, Robert Cervero, William Garrison, and John Landis for comments on drafts of the doctoral dissertation on which this paper is based (*41*).

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Publication of this paper sponsored by Committee on Transportation and Land Development.