How Density and Mixed Uses at the Workplace Affect Personal Commercial Travel and Commute Mode Choice

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A high density of shops and services near the workplace may make it easier to carry out personal commercial activities on foot before, during, and after work, enabling reduced vehicle use during the rest of the day. Investigating this question is an important addition to the current research, which has focused on residential neighborhoods. Data from the 1995 Nationwide Personal Transportation Survey are used to investigate the influence of workplace employment density and share of retail employment on commute mode choice and vehicle miles traveled (VMT) to access personal commercial activities. The analysis controls for socioeconomic characteristics and accounts for the endogeneity of commute mode choice and personal commercial VMT by employing a joint logit-Tobit model. Employment density at the workplace is found to be associated with a lower likelihood of automobile commuting and reduced personal commercial VMT, while the presence of employment in the retail category does not play a significant role. Workplace density is more clearly related to reduced VMT and automobile commuting than to characteristics of workers' residential neighborhoods and could have significant influences on personal commercial VMT and automobile commuting when increasing over a large area. The results suggest that land use planners should focus on encouraging employment density to a greater extent than is the current practice, although further research is needed on the role played by correlated factors such as higher parking costs, increased road congestion, and better transit service.

Many urban planners want to facilitate high-density, mixed-use land development to make alternative transportation modes more attractive. The theory is that higher development density and reduced segregation of land uses should reduce the distance between the location of activities that require travel. In turn, shorter trips are thought to be more likely carried out on foot or via transit. Urban planning policies intended to effect denser, more mixed development include relaxation of parking requirements, so-called density bonuses, minimum floor-to-area ratio requirements, and transit-oriented development programs.

This research investigates the relationships between the built environment characteristics of the workplace, worker commute mode choice, and workers' use of personal vehicles to carry out personal commercial activities. Shops and services near the workplace may make it easy for workers to carry out activities on foot before, during, and after the workday, such as buying flowers or gifts, taking clothes to the dry cleaner, visiting the dentist, going out to lunch, and catching a movie after work. Those who take advantage of this pedestrian accessibility may travel fewer vehicle miles to carry out such activities during the rest of the day.

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Workers who have a car available at the workplace are probably less likely to patronize nearby shops and services. At the same time, the choice of whether to drive to work may be conditioned on the availability of those shops and services. Understanding this interrelatedness is important for planners who claim that particular land use policies have positive transportation system benefits.

Because workers make relatively few discretionary trips on workdays, the potential impact of workplace land use on travel behavior might be thought to be minimal. But there are two important reasons to investigate the relationship.

First, it may be pragmatically and politically more acceptable to change policies in primarily nonresidential areas, because the users of those areas may have fewer complaints about more intense development than residential users typically do. Furthermore, in employment clusters of large cities, existing policies may significantly constrain development density.

Second, researchers can have greater confidence in analysis that focuses on how the built environment at the workplace affects travel. People who prefer to use alternative modes may choose to live in dense mixed-use neighborhoods, which are often more walkable and have better access to transit. If so, typical regression methods relating their travel behavior to residential land use characteristics will have results that must be interpreted with a great deal of caution (*1*). But workers are less likely to choose their jobs based on workplace land use characteristics. Thus, any relationships found in such analysis can be interpreted with greater confidence that they represent the independent effects of land use, instead of self-selection effects.

PREVIOUS RESEARCH

Much of the recent research on urban form and travel behavior has focused on the question of whether people living in dense, mixed-use neighborhoods with traditional street grids make fewer trips by private automobile (*1–5*). Recent improvements in this line of research have included correcting for endogeneity of the residential location decision and the tendency to use a car for trips (*5*, *6*) and including trip speeds and distances as explanatory variables in a two-stage least-squares procedure (*7*). There has been relatively little recent research on how workplace land use affects travel behavior other than a study showing that commute mode choice can be affected to a modest extent by workplace transportation demand management programs and site-specific land use mix (*8*).

Age, sex, race, education, income, and household life cycle (e.g., presence of children in the household) have been found to be associated with particular patterns of mode choice and total travel (*9–13*) and are included in this analysis. Including information on recent immigrant status (*14*) and parental status (*9*) is not possible with this data set.

The analysis presented here varies in other ways from earlier research. First, the focus is narrowed to personal commercial travel, which should be more directly related to the accessibility of commercial activities than other types of nonwork trips. Second, the analysis accounts for the simultaneity of commute mode choice and day-long participation in personal commercial activities, while correcting for the fact that the dependent variable is left-censored.

DATA AND SAMPLE SELECTION

The data set is drawn from the Person and Travel Day Trip files of the 1995 Nationwide Personal Transportation Survey (NPTS). The initial data set consists of 34,560 workers with complete work periods and complete mileage information. Within this group the test sample is restricted to those who identify themselves as drivers (95% of the sample), have at least one car available for every driver in the household (85%), and state that transit service is available near their residences (64%). These restrictions are intended to substantially increase the likelihood that each individual included in the analysis has a complete set of mode choices for the commute. Also, respondents in the upper 1% of personal commercial vehicle miles traveled (VMT) (greater than about 50 mi) are excluded. Based on an inspection of the data set, the reporting appears to be error-prone for outlying values.

The omission of individuals who report that bus service is not available deserves comment. The omitted group may contain many who are ignorant of bus service, perhaps due to a strong preference for driving. However, comparing values of the independent and dependent variables before and after dropping these individuals does not reveal any obvious selection bias. Differences between the initial sample and the truncated estimation sample are presented in Table 1.

Table 2 presents the mean and variance of the independent variables in the estimation sample for respondents who drove to work and those who did not. Those who drove to work averaged almost a mile more per day in personal commercial VMT, and their average workplace density, at about 6,000 workers per square mile, is far lower than the nondriving group average of 14,500 per square mile.

METHODOLOGY

Definition of Personal Commercial VMT

Personal commercial VMT is defined as the number of miles traveled in a personal vehicle for personal commercial purposes. The category includes shopping (over half the total), medical/dental, going out to

TABLE 1 Comparison of Samples Before and After Truncation

	Before truncation (N=30,587)		After truncation (N=14,478)		
Variable	Mean	St Dev	Mean	St Dev	Description
pcdmitot	4.678	12.820	3.988	7.322	vehicle miles traveled on personal commercial trips
D	0.84		0.93		drove to work (dummy)
wtempldn	5.8	13.9	6.3	13.8	employees per square mile, workplace Census tract (1,000s)
wtindret	13.246	14.116	13.782	14.427	employment share retail, workplace Census tract (percent)
wtempz	*0.285*		*0.257*		*missing workplace Census tract data (dummy)*
hbhresdn	1.615	1.782	1.902	1.693	housing units per square mile, residential block group (1,000s)
hteempdn	1.097	1.464	1.312	1.458	employees per square mile, residential Census tract (1,000s)
htindret	20.92	13.88	22.32	14.63	employment share retail, residential Census tract (percent)
hbtz	*0.01*		*0.01*		*missing residential Census block group data (dummy)*
disttowk	11.20	14.85	10.94	15.68	reported one-way distance to work (mi)
wktm_tot	466.03	184.81	471.17	182.43	total time spent at work (minutes)
r_age	39.47	12.73	40.09	12.21	age
female	0.47		0.46		female (dummy)
afram	0.06		0.06		African American (dummy)
asian	0.02		0.02		Asian American (dummy)
oth_race	0.05		0.04		other non-Anglo race (dummy)
nohs	0.08		0.05		less than high school degree (dummy)
somecoll	0.27		0.28		more than high school degree (dummy)
income	41.44	29.42	43.92	29.86	household income (1,000s)
incomez	*0.16*		*0.15*		*missing household income data (dummy)*
hh1	0.13		0.15		one-adult household (dummy)
kids	0.53		0.48		household with children (dummy)
carprdvr	1.00	0.41	1.11	0.30	cars per driver in household
hhsize	3.11	1.35	2.92	1.30	household size

SOURCE: 1995 Nationwide Personal Transportation Survey. Sample before truncation consists of all self-reported workers living in a CMSA with complete work periods on the survey day. The after-truncation sample consists of the subgroup who report that bus service is available, who live in households with at least one vehicle per licensed driver, who are self-reported drivers, and who travel 50 miles or less for personal commercial purposes.

TABLE 2 Comparison of Subgroups: Automobile Commuters and Other Workers (Drivers with Complete Work Periods, Car Access, and Transit Access)[a]

Variable	Did not drive to work (N=1,075) Mean	St Dev	Drove to work (N=13,403) Mean	St Dev	Description
pcdmitot	3.132	6.837	4.057	7.355	vehicle miles traveled on personal commercial trips[b]
wtempldn	14.575	22.764	5.606	12.629	employees per square mile, workplace Census tract (1,000s)
wtindret	11.4	12.9	14.0	14.5	employment share retail, workplace Census tract (percent)
wtempz	*0.277*		*0.255*		*missing workplace Census tract data (dummy)*
hbhresdn	2.643	2.038	1.843	1.648	housing units per square mile, residential block group (1,000s)
hteempdn	1.804	1.737	1.273	1.426	employees per square mile, residential Census tract (1,000s)
htindret	21.5	13.9	22.4	14.7	employment share retail, residential Census tract (percent)
hbtz	*0.004*		*0.006*		*missing residential Census block group data (dummy)*
disttowk	11.785	31.621	10.871	13.615	reported one-way distance to work (mi)
wktm_tot	515	257	468	175	total time spent at work (minutes)[c]
r_age	39.6	12.6	40.1	12.2	age
female	0.50		0.45		female (dummy)
afram	0.10		0.05		African American (dummy)
asian	0.03		0.02		Asian American (dummy)
oth_race	0.05		0.04		other non-Anglo race (dummy)
nohs	0.07		0.05		less than high school degree (dummy)
somecoll	0.27		0.28		more than high school degree (dummy)
income	43.321	31.020	43.970	29.760	household income (1,000s)
incomez	*0.15*		*0.15*		*missing household income data (dummy)*
hh1	0.19		0.15		one-adult household (dummy)
kids	0.44		0.49		household with children (dummy)
carprdvr	1.09	0.32	1.11	0.29	cars per driver in household
hhsize	2.84	1.36	2.93	1.29	household size

Bold type signifies exogenous variables used only in the logit equation (step 1 of model 2). All other variables are used in both equations.

NOTES: [a] Car accessibility defined as one or more personally owned vehicles per driver in household. Bus accessibility defined using "bus_avl" variable in Travel Day Trip File (nonresponses also dropped).
[b] Personal commercial trips defined as NPTS trip purposes "shopping," "medical/dental," "going out to eat," and "other social/recreational." Variable calculated using "trpmiles" and "trptrans," variables in NPTS Travel Day Trip file.
[c] Variable calculated using activity duration ("dweltim2") and trip purpose ("whytrip95") data from Travel Day Trip File.

SOURCE: 1995 Nationwide Personal Transportation Survey.

eat, and other social/recreational trips. Ignoring return trips home, personal commercial trips made up 39% of trips in the unweighted national sample.

Independent Variables for VMT Models

Independent variables for the VMT models are presented in Table 2. The test variables are workplace census tract employment density and share of retail employment. In the NPTS, this information is represented categorically. Here, the information has been recoded at center points of the categories and treated as a continuous variable. Similarly, three variables proxying land use at the residential location are included: block group housing unit density, employment density, and share of retail employment.

Control variables include sex, age, race/ethnicity, household income, education, household size, and dummy variables indicating whether the household has only one adult and whether children under age 17 are present. The distance from the residence to the workplace and the amount of time spent at work are also included. Increased distance to the workplace is expected to increase the relative convenience of an automobile for the commute and hence the likelihood that an automobile will be used both for the commute and for carrying out personal commercial activities. By reducing discretionary time, the length of the work period is expected to decrease the amount of personal commercial activity and hence personal commercial VMT.

Treatment of Missing Data

Like most data sets, the NPTS lacks complete responses for some variables. To account for respondents with missing information, instead of merely deleting cases from the analysis, the missing indicator method is used (*15*). A dummy variable, created to indicate missing values for each relevant variable, is set equal to 1 for respondents missing the data and to 0 otherwise. This procedure is followed for household income [represented by the variable (incomez)], workplace land use characteristics (wtempz), and residence area land use characteristics (hbtz). The problem is most extensive with the workplace census tract employment data, with missing values for 26% of the estimation sample (see Table 2).

Additional Variables for Car Commuting Model

In addition to the independent variables used in the VMT models, variables are included in the model for whether a motorized vehicle was driven to work. First, race and Hispanic status are included. These characteristics are typically seen as directly related to automobile use even when controlling for income (*16*). However, in some accounts, once automobile ownership is controlled for, race effects disappear (*17*). In initial testing, the race variables were not strongly related to personal commercial VMT, but African American status was negatively related to the likelihood of driving to work even when controlling for transit access. Therefore, the race variables were included as exogenous variables, reflecting the hypothesis that cultural differences for which racial/ethnic status is a proxy affect commute mode preferences.

Second, a variable denoting the number of cars per driver in the household is included. Recall that the sample is restricted to those in households with at least one car per driver. The car per driver variable thus can be interpreted as indicating a household taste for cars instead of strictly as an indicator of access to the automobile mode.

Finally, four other variables relating to transportation infrastructure are included to model the commute mode choice: whether the individual must pay to park at work (7% of the sample); a dummy variable indicating that the nearest transit stop is more than 2 mi from the residence (17%); distance to the nearest transit stop (whether bus, streetcar, commuter rail, or subway) for stops within 2 mi of the residence; and a dummy variable indicating whether streetcar or subway service is reported available, which may indicate a higher-quality metropolitan transit system (9%). The transit system variables are plausibly exogenous to personal commercial VMT because transit is rarely used for personal commercial trips; the primary hypothesis is that dense, mixed-use workplaces enable walk trips to be substituted for driving trips.

Hypothesis Testing

Two methodological complications arise in testing the relationship between workplace land use and personal commercial VMT. First, only 52% of respondents on the survey day drive to access personal commercial activities (Figure 1). Because time is likely to be scarce on a workday, there is a latent tendency to conserve time by traveling less for other purposes. At its maximum, this tendency can be expressed only by not traveling at all. As a result, the dependent variable, personal commercial VMT, is left-censored, and estimating an ordinary least-squares model on the sample will yield biased estimates. Second, an important predictor of personal commercial VMT by workers is whether a car was used to commute to work. However, for workers with access to cars, the decision to commute to work in turn depends on the planned extent of participation in personal commercial activities and the anticipated location of those activities (Figure 2).

The analysis addresses these complications by two approaches. To correct for a biased error term due to the censored dependent variable, a Tobit regression is used. To account for the simultaneity of the commute mode choice and personal commercial VMT, a selectivity correction approach, essentially equivalent to two-stage least squares, is also used. These approaches have rarely, if ever, been used together in the academic literature.

For the purpose of illustration, a straightforward Tobit model is estimated first, in which personal commercial VMT is specified as a function of the independent variables. The Tobit is used to account for

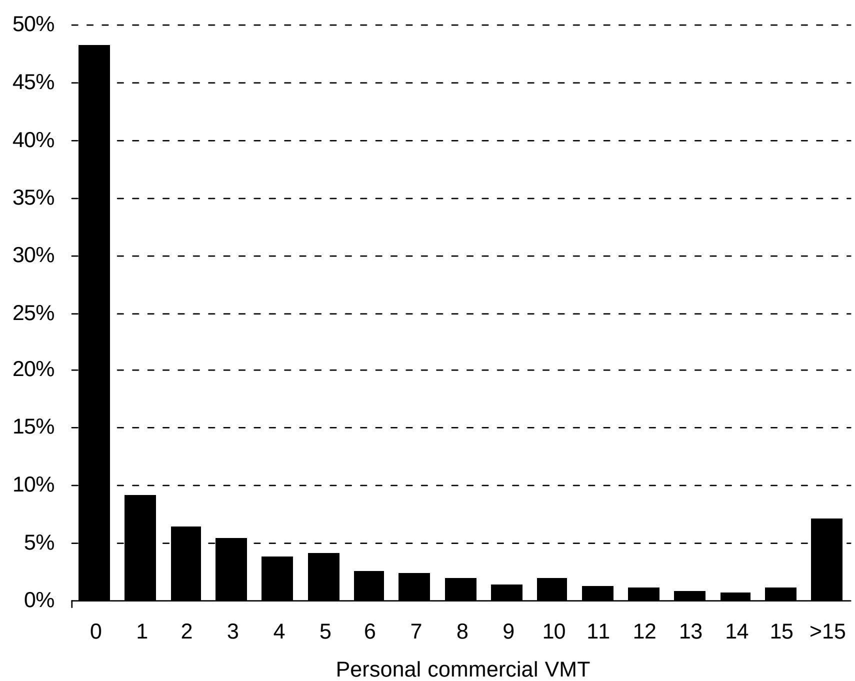

FIGURE 1 Personal commercial VMT by share of workers.

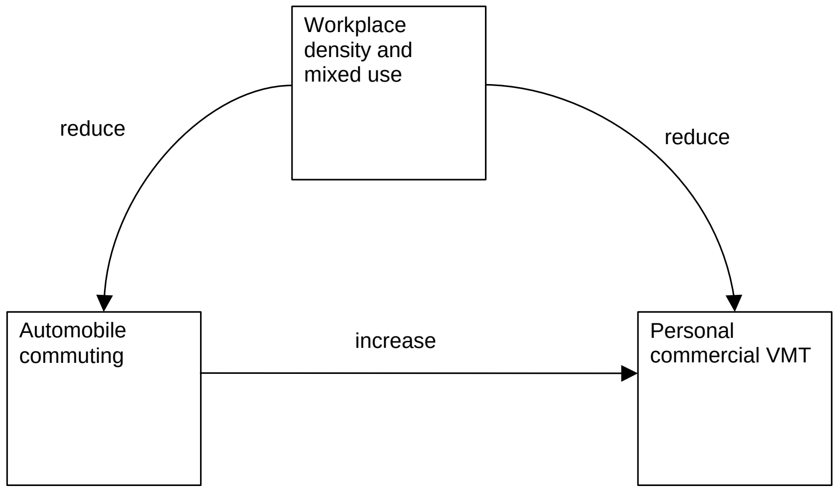

FIGURE 2 **Conceptual model.**

the fact that the dependent variable is left-censored. Second, a joint logit-Tobit model is estimated, in which personal commercial VMT and the choice of whether to drive to work are understood as simultaneous, following the selectivity correction procedure in Train (*18*). By including this term in the Tobit model, it is corrected for endogeneity. The procedure is similar to that followed by Giuliano and Lave (*19*).

Simple Continuous Model with Tobit Correction

The first model can be thought of as two separately estimated equations on each of two subsamples: those who did not drive to work, and those who did. The dependent variable **y** is personal commercial VMT. The model can be represented with an equation for each subsample:

$$\mathbf{y}_{nca} = \beta \mathbf{X}_{nca} + \epsilon_{nca} \tag{1a}$$

$$\mathbf{y}_{ca} = \alpha_{ca} + \beta \mathbf{X}_{ca} + \epsilon_{ca} \tag{1b}$$

where

$\mathbf{y}_{nca}$ and $\mathbf{y}_{ca}$ = vectors of dimension 1 by n_{nca} and 1 by n_{ca}, respectively;
n_{ca} = subset of individuals who drove to work;
n_{nca} = subset who did not drive to work;
$\mathbf{X}_s$ = an n_s-by-k matrix of k independent variables for n_s individuals;
β = vector of coefficients to be estimated;
α_{ca} = fixed effect of having a car available at work on personal commercial VMT; and
ϵ_s = vectors of normally distributed error terms with each term equivalent, under the identically and independently distributed assumption.

This model can then be represented in a pooled form:

$$\mathbf{y} = \gamma \mathbf{Z} + \epsilon \tag{2}$$

where

$\mathbf{y}$ = vector of dimension 1 by m formed by stacking $\mathbf{y}_{ca}$ and $\mathbf{y}_{nca}$ (where $m = n_{ca} + n_{nca}$),
ϵ = vector of dimension 1 by m (ϵ_{ca} and ϵ_{nca} are stacked to make ϵ of dimension 1 by m) (and ϵ_{ca} is assumed to equal ϵ_{nca} for all n), and
$\mathbf{Z}$ = m by $(k+1)$, composed of $\mathbf{X}_{ca}$ and $\mathbf{X}_{nca}$ plus a column vector consisting of a dummy variable set equal to 1 for those who drove to work and 0 otherwise.

This censored dependent variable requires estimation with censored regression techniques. The Tobit regression can be carried out with the following form (*20*) in which *i* is an observation subscript:

$$y_i = \gamma' z_i + \sigma \frac{\phi_i}{\Phi_i} + \epsilon_i \tag{3}$$

The ratio in the second term can be estimated by using a separate probit regression to get values of φ_i and Φ_i, which are the normal probability density function and cumulative density function, respectively, evaluated at $\gamma z_i/\sigma$.

The dependent variable in the probit is a dummy equal to 1 if personal commercial VMT is 0 and equal to 0 if personal commercial VMT is positive. The independent variable is the same vector used in the ordinary least-squares (OLS) equation, whose coefficients are equal to γ/σ. Equation 3 can then be estimated as an OLS regression in which σ is a coefficient.

Stata's "Tobit" command is used to estimate σ. This preprogrammed routine uses a maximum likelihood procedure (*21*, pp. 138, 145, 146), which is asymptotically equivalent to estimating Equation 3 by ordinary least squares but is more efficient.

Joint Discrete/Continuous Tobit Model

The joint model is sequentially estimated as follows. First, a logit regression is calculated with a dependent variable equal to 1 if the individual drove to work and 0 otherwise. The logit model uses all the independent variables used in the VMT model as well as a number of additional independent variables, as explained in an earlier section.

In the second step, a selectivity correction term, $E(\epsilon_s)$, is added:

$$\mathbf{y}_{nca} = \beta \mathbf{X}_{nca} + E(\epsilon_{nca}) + \eta_{nca} \tag{4a}$$

$$\mathbf{y}_{ca} = \alpha_{ca} + \beta \mathbf{X}_{ca} + E(\mathbf{e}_{ca}) + \eta_{ca} \tag{4b}$$

where $E(\epsilon_s)$ is nonzero and varies by person, assuming that the choice of commute mode and how many miles to drive for personal commercial activities are related.

For each person $E(\epsilon_{ca})$ is estimated by the following equation by property of the logit model (*18*, Equation 5.11):

$$E(\epsilon_{ca}) = \frac{-\sqrt{6\sigma^2}}{\pi}\rho_{ca}\left(\frac{P_{nca}\times\ln P_{nca}}{1-P_{nca}}+\ln P_{ca}\right) \tag{5}$$

where

σ^2 = variance of ϵ,
ρ_{ca} = mutual correlation of car ownership and miles traveled with unobserved characteristics of the person, and
P_{ca} = probability of driving to work.

In the binomial case, $E(\epsilon_{nca})$ is a symmetric expression with the preceding (*18*, p. 4), and ρ_{nca} is just $1 - \rho_{ca}$.

The term in brackets is calculated by using estimated probabilities from the logit model and is therefore stochastic, but it is treated as a nonstochastic independent variable in the estimation of the next step. Therefore, the reported standard errors will be too small.

Similar to the simple continuous model, the data are pooled as follows:

$$\mathbf{y} = \gamma\mathbf{Z} + E(\epsilon) + \eta \tag{6}$$

In the pooled sample, the bracketed term in Equation 5 varies depending on which subsample the individual belongs to. Following Giuliano and Lave (*19*, p. 158), this selectivity correction term (SEL) can be written as follows:

$$C \times E(\epsilon_{ca}) - (1 - C) \times E(\epsilon_{nca}) = \text{SEL} \tag{7}$$

where C is a dummy variable set equal to 1 for individuals in households with at least one vehicle per driver and 0 otherwise.

Then,

$$E(\epsilon) = \zeta \times \text{SEL} \tag{8}$$

where ζ is the coefficient to be estimated as part of Equation 6, equal to the term outside the brackets in Equation 5.

The final addition to the model is to add a term reflecting the correction for left-censoring of the dependent variable. The resulting equation has two correction terms: the selectivity correction term that accounts for the simultaneous choice of whether to drive to work and how much personal commercial travel to carry out by car, and the term correcting for the censored dependent variable:

$$y_i = \gamma' z_i + \zeta \times \text{SEL} + \sigma\frac{\phi_i}{\Phi_i} + \eta \tag{9}$$

Equation 9 is estimated by using Stata's Tobit command.

Test of Robustness of Selectivity Correction Approach

The selectivity correction approach is unbiased but inefficient because it is sequentially estimated. Its robustness can be determined by assuming that the true model is not endogenous and testing whether the approach might incorrectly support the null hypothesis. This was done with a Monte Carlo simulation: setting the coefficient on SEL equal to zero; using other coefficients from the empirical model to predict automobile ownership and personal commercial VMT; calculating estimates of the empirical mean and standard deviation of ζ, the coefficient on SEL; and testing whether the calculated coefficient was significantly different from zero. For a sample of 20 replications, the estimated empirical mean was –0.24, with an estimated standard deviation of 0.32, yielding a *t*-statistic of about 0.67. Thus, the coefficient is not significantly different from zero with any level of confidence for this sample. With a sample of 50 replications, the estimated empirical mean was –0.36, with an estimated empirical standard deviation of 0.363, yielding a *t*-statistic of about –1.0, again statistically indistinguishable from zero. The results of the test support the finding that the choice to commute to work by car and the amount of personal commercial VMT are simultaneously determined.

MODEL RESULTS

Table 3 reports regression results for the uncorrected Tobit model, in which the decision to drive to work ($D = 1$) is treated as an independent variable that is unrelated to workplace density, share of retail, and other independent variables included in the model. Controlling for other correlates, the results show that those who drive to work travel, on average, 1.6 mi more per day via personal vehicle for personal commercial purposes. Higher workplace employment density is associated with slightly reduced personal commercial VMT at a high level

TABLE 3 Personal Commercial VMT Regressed on Land Use and Demographic Variables (Simple Continuous Model with Tobit Correction)

Variable	Coef.	Std. Err.	z	P>|z|	95% Conf. Interval	
D	1.574	0.435	3.623	**0.000**	0.723	2.426
wtempldn	-0.050	0.009	-5.639	**0.000**	-0.067	-0.033
wtindret	-0.007	0.009	-0.794	0.427	-0.026	0.011
wtempz	-1.572	0.321	-4.891	**0.000**	-2.203	-0.942
disttowk	0.022	0.007	3.205	**0.001**	0.009	0.036
hbhresdn	-0.176	0.081	-2.185	**0.029**	-0.334	-0.018
hbtz	0.369	1.391	0.265	0.791	-2.358	3.096
hteempdn	-0.173	0.0924	-1.867	0.062	-0.354	0.009
htindret	0.004	0.007	0.569	0.569	-0.010	0.019
wktm_tot	-0.013	0.001	-21.264	**0.000**	-0.014	-0.012
r_age	-0.018	0.009	-1.975	**0.048**	-0.036	0.000
nohs	-1.716	0.527	-3.256	**0.001**	-2.750	-0.683
somecoll	0.588	0.240	2.451	**0.014**	0.118	1.058
income	0.097	0.019	5.227	**0.000**	0.061	0.133
income2	-0.0006	0.0001	-3.797	**0.000**	-0.0008	-0.0003
incomez	1.912	0.549	3.484	**0.000**	0.836	2.987
female	0.589	0.217	2.709	**0.007**	0.163	1.015
hh1	1.663	0.365	4.554	**0.000**	0.947	2.378
kids	-0.685	0.326	-2.102	**0.036**	-1.324	-0.046
hhsize	-0.007	0.141	-0.052	0.959	-0.283	0.268
_cons	2.533	0.968	2.618	**0.009**	0.636	4.430
_se	11.5392	0.10216		(sigma-hat)		

Log-likelihood -33,425.517; 14,478 observations; likelihood ratio test with $\chi^2_{(20)} = 707.840$; Prob > $\chi^2 = 0.0000$; Pseudo-$R^2 = 0.0105$.

Observation summary: 6,998 left-censored observations at pcdmitot ≤ 0; 7,480 uncensored observations.

Note: Bolded variables are significant at the 95 percent confidence level.

of statistical significance but with relatively modest magnitude. The coefficient of –0.05 means that each additional 10,000 employees per square mile in workplace density (an addition of about 15 employees per gross acre) is associated with an average half-mile reduction in personal commercial VMT per capita. Although the share of retail at the workplace is also negatively related to personal commercial VMT, the relationship is weak and not statistically significant.

Other variables in the model have the expected signs. Higher residential density decreases personal commercial VMT: every additional 1.5 housing units per gross acre (1,000 units per square mile) is associated with a 0.2-mi reduction in personal commercial VMT. However, neither employment density nor the share of retail in the residential census tract is related to personal commercial VMT in a statistically significant sense. Total time spent at work and the presence of children in the household are both associated with reduced personal commercial VMT, suggesting that reduced discretionary time for such activities may be a cause. By the same token, individuals in one-person households, with fewer household responsibilities, travel significantly more for personal commercial purposes than others. Higher income increases personal commercial VMT, with a declining increase reflected in the significant coefficient on the income squared variable (income2), while those living in older households have lower personal commercial VMT. Finally, women drive farther than men for personal commercial purposes, which is generally consistent with literature relating gender roles to household responsibilities.

The joint logit–Tobit model is presented in Tables 4 and 5. Table 4 presents logit regression results from the commute choice stage. The dependent variable is a dummy variable set equal to one for those who drove to work. Two of the instruments have an individually significant effect on the likelihood of driving to work: subway/streetcar availability (rail) significantly decreases the likelihood, and, unexpectedly, having to pay to park (paypark) is correlated with an increased likelihood of driving to work. Most of the highly significant variables in the continuous model also are important in the second model; clearly, there is reason to believe the choices are endogenous.

Table 5 presents results for the second stage, incorporating the selectivity correction term in a Tobit regression on personal commercial VMT. Taken together, the results from Tables 4 and 5 are instructive, pointing to two separate effects of workplace density.

First, workplace employment density is associated with a lower likelihood of car commuting, as reflected in the coefficient on wtempldn in Table 4, which suggests that each increase of 1.5 employees per gross acre (i.e., 1,000 employees per square mile) at the workplace decreases the probability of using an available car for commuting by about 3%.

Second, as indicated in Table 5, workplace employment density is associated with reduced personal commercial VMT regardless of whether a car was used to commute to work. The corrected VMT relationship is half as strong as that found by the uncorrected Tobit approach: an increase of employment density of 15 employees per acre (10,000 employees per square mile) reduces per capita personal commercial VMT by 0.25 mi. Apparently, much of the influence of employment density on personal commercial VMT is actually indirect, mediated by its effect on the choice of whether to drive to work. For the same reason, the coefficient on D (equal to 1 for those driving to work) has increased a great deal in comparison to Table 3, up to more than 9 mi per day, reflecting the fact that several influences of independent variables in the VMT model are mediated through commute mode choice.

TABLE 4 Car Commute Choice Regressed on Land Use, Demographic, and Instrumental Variables (Logit, First Stage of Joint Discrete/Continuous Model)

Variable	Coef.	Std. Err.	z	P>|z|	[95% Conf.Interval]	
afram	-0.175	0.121	-1.453	0.146	-0.412	0.061
asian	0.024	0.207	0.114	0.909	-0.382	0.430
oth_race	-0.021	0.166	-0.129	0.897	-0.347	0.304
lhh_hi_2	-0.069	0.170	-0.406	0.685	-0.401	0.264
lhh_hi_3	0.724	1.051	0.689	0.491	-1.335	2.784
carprdvr	0.077	0.117	0.659	0.510	-0.152	0.306
parkpay	0.422	0.126	3.341	**0.001**	0.174	0.669
trnsdist	0.018	0.026	0.665	0.506	-0.034	0.069
trnsdisz	-17.380	26.339	-0.660	0.509	-69.004	34.243
farstop	0.068	0.180	0.380	0.704	-0.285	0.421
rail	-0.305	0.101	-3.017	**0.003**	-0.504	-0.107
wtempldn	-0.032	0.002	-15.164	**0.000**	-0.036	-0.027
wtindret	0.001	0.003	0.379	0.705	-0.005	0.007
wtempz	-0.484	0.101	-4.784	**0.000**	-0.682	-0.285
disttowk	-0.003	0.002	-1.711	0.087	-0.006	0.0004
hbhresdn	-0.125	0.023	-5.386	**0.000**	-0.170	-0.080
hbtz	0.250	0.526	0.476	0.634	-0.781	1.282
hteempdn	-0.034	0.026	-1.321	0.187	-0.085	0.017
htindret	0.003	0.002	1.372	0.170	-0.001	0.008
wktm_tot	-0.001	0.000	-7.719	**0.000**	-0.002	-0.001
r_age	0.003	0.003	0.930	0.352	-0.003	0.008
nohs	-0.503	0.136	-3.700	**0.000**	-0.769	-0.236
somecoll	-0.013	0.075	-0.172	0.863	-0.160	0.134
income	0.021	0.005	3.989	**0.000**	0.011	0.032
income2	0.000	0.000	-3.737	**0.000**	-0.0002	-0.0001
incomez	0.560	0.157	3.558	**0.000**	0.252	0.869
female	-0.264	0.067	-3.930	**0.000**	-0.396	-0.133
hh1	0.012	0.109	0.115	0.909	-0.201	0.226
kids	0.164	0.100	1.645	0.100	-0.031	0.359
hhsize	-0.038	0.042	-0.887	0.375	-0.120	0.045
_cons	3.337	0.331	10.090	**0.000**	2.689	3.985

Log-likelihood -3526.5627; 14,478 observations; likelihood ratio test with $\chi^2_{(30)}$ = 605.67; Prob > χ^2 = 0.0000; Pseudo-R^2 = 0.0791.

Note: exogenous variables appear in the upper tier. Bolded variables are significant at the 95 percent confidence level.

A similar effect occurs for housing density on the residential side. An additional 1.5 units per gross acre (1,000 units per square mile) is associated with a 12% lower likelihood of car commuting, but the direct effect of residential density on personal commercial VMT is statistically indistinguishable from zero. This is a very interesting result—it suggests that residential density may be more important in determining commute mode choice than in directly influencing overall personal commercial VMT, at least on workdays.

Note that the pseudo-R^2 statistic for the VMT models is extremely low, at about 0.01. Because travel behavior is largely idiosyncratic and can vary a great deal on a day-to-day basis, this is not altogether surprising.

Finally, respondents missing data on workplace land use and household income are systematically different from the rest of the sample. Individuals with unreported workplace land use data (wtempz equal to 1) are substantially more likely not to use a car to go to work, and those refusing to report their income travel substantially more miles for personal commercial purposes (see Tables 3 and 5). This describes a caveat with the data set that would go unreported if those cases were simply deleted, as is the current practice, and suggests a need for further research, as discussed in the following section.

TABLE 5 Personal Commercial VMT Regressed on Land Use and Demographic Variables (Tobit, Second Stage of Joint Discrete/Continuous Model)

Variable	Coef.	Std. Err.	z	P>|z|	95% Conf. Interval	
D	9.656	2.554	3.780	**0.000**	4.649	14.663
SEL	2.130	0.662	3.217	**0.001**	0.832	3.428
wtempldn	-0.025	0.012	-2.171	**0.030**	-0.048	-0.002
wtindret	-0.007	0.009	-0.742	0.458	-0.025	0.011
wtempz	-1.296	0.333	-3.895	**0.000**	-1.948	-0.644
disttowk	0.024	0.007	3.481	**0.001**	0.011	0.038
hbhresdn	-0.082	0.086	-0.962	0.336	-0.250	0.085
hbtz	0.306	1.390	0.220	0.826	-2.419	3.031
hteempdn	-0.142	0.093	-1.532	0.126	-0.324	0.040
htindret	0.002	0.007	0.262	0.793	-0.013	0.016
wktm_tot	-0.012	0.001	-18.874	**0.000**	-0.014	-0.011
r_age	-0.020	0.009	-2.139	**0.032**	-0.037	-0.002
nohs	-1.416	0.535	-2.645	**0.008**	-2.466	-0.367
somecoll	0.599	0.240	2.499	**0.012**	0.129	1.069
income	0.085	0.019	4.487	**0.000**	0.048	0.122
income2	0.000	0.000	-3.121	**0.002**	-0.001	0.000
incomez	1.604	0.557	2.880	**0.004**	0.512	2.695
female	0.715	0.221	3.235	**0.001**	0.282	1.148
hh1	1.672	0.365	4.578	**0.000**	0.956	2.388
kids	-0.774	0.327	-2.368	**0.018**	-1.415	-0.133
hhsize	0.016	0.141	0.117	0.907	-0.260	0.293
_cons	-5.446	2.667	-2.042	**0.041**	-10.673	-0.218
_se	11.537	0.102		(sigma-hat)		

Log-likelihood -33,420.298; 14,478 observations; likelihood ratio test with $\chi^2_{(21)} = 718.28$; Prob > $\chi^2 = 0.0000$; Pseudo-$R^2 = 0.0106$.

Observation summary: 6,998 left-censored observations at pcdmitot ≤ 0; 7,480 uncensored observations.

Note: Bolded variables are significant at the 95 percent confidence level.

CONCLUSIONS

Compared with a simple continuous model, the joint discrete-Tobit model provides a better understanding of how employment land use affects personal commercial VMT. First, higher employment density is associated with a lower likelihood that a worker will drive to work, which in turn is associated with lower personal commercial VMT. Second, workplace density is also directly associated with reduced personal commercial VMT, regardless of commute mode choice. These effects are modest but highly significant in a statistical sense, and there is little reason to suspect that the result is an artifact of a self-selection process, both because the workplace instead of the residential location is the subject of investigation, and because all workers in the data set have at least one car per driver in their households.

The net effect over a large number of individuals in a city is likely substantial. Assume that a 1-mi^2 area of a city contains 5,000 employees. The analysis suggests that an increase in density of about 3,000 employees in this area would be associated with a 9% decrease in the automobile commute mode share and a reduction in personal commercial VMT of a bit more than a mile per day per worker, or almost 9,000 VMT per day—without even accounting for lower VMT from reduced automobile commuting. There may be concomitant increases in personal commercial VMT on weekends or by other household members, phenomena that are not investigated here. Nevertheless, if nothing else, this research strongly supports the notion that urban planners should pay attention to the characteristics of downtowns, job centers, and other primarily nonresidential parts of urban areas, because planning policies in such areas may have stronger influences on mode choice than residentially based interventions.

The results also suggest that residential density is correlated with transit and walking convenience for the commute but does not directly influence personal commercial VMT. However, because the model does not correct for the potential endogeneity of residential location choice, residential density, and commute mode choice, the relatively large effect of the relationship with commute mode choice is probably overstated.

Retail share, intended as a proxy for mixed-use development, does not enter significantly into the model on either the workplace or the residential side. Two possible explanations for this finding come to mind. First, the retail employment share may be a poor measure of accessibility of activities at the workplace, particularly if very high concentrations of retail shops drive out nonretail activities that might be more valued by workers during the work day, such as restaurants, banks, and dry cleaners.

Second, the strongest effects of development density may not be related to increased accessibility of activities via walk and transit. Instead, other forces may be at work. A number of researchers in this area have noted that development density in analysis of this sort may be a proxy for unobserved variables such as metropolitan-wide transit and walking accessibility, high road congestion, and high parking costs (*22*). Parking availability has been argued to be a particularly important determinant of travel choices (*23*). Because most of the high-density workplaces in the sample are in places like New York and Chicago, where these characteristics are likely common, such a correlation may be at work in this data set. If so, this analysis suggests that urban policies to relax density constraints in primarily nonresidential areas are likely to be most successful when accompanied by concomitant changes in those associated factors.

SUGGESTIONS FOR FUTURE RESEARCH

As noted, the significant relationship found between workplace density and personal commercial VMT may be partially due to factors correlated with, or even caused by, nonresidential development density. This suggests several important research questions for further examination. First, to what extent is workplace development density associated with higher parking costs, better pedestrian walking environments, higher-quality transit, greater road congestion, or other possible influences on travel? Second, assuming such correlations are strong in U.S. cities, to what extent do these factors account for the apparent downward influence of employment density on VMT? Finally, to what extent can one expect the lifting of planning constraints on nonresidential development density (such as minimum floor-to-area ratio requirements) to result in increases in employment density along with these correlated factors?

Because the NPTS lacks an explicit spatial component, it is impossible to enrich the data set with additional spatial information below the metropolitan statistical area level. Replicating this research by using regional travel diaries is essential to understanding the relationships more deeply, although some results are likely to be region specific. For example, this could make it possible to include all individuals in the data set with nearby transit access, not relying on respondents to accurately report such availability.

Finally, the treatment of missing data in this analysis indicates a larger problem with previous analysis of this sort that could be addressed in future research. The missing indicator method reveals that deleting respondents without complete income or workplace information would significantly bias the results. More sophisticated methods, such as data imputation, are preferable when the missing indicator method shows that subgroups with missing information appear to be different in some way (*24, 25*). Such treatment of missing data should be an integral part of the future analysis of travel data sets and apparently has rarely been considered to date.

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