

The Impact of Urban Form on Vehicle Miles Traveled:

An Econometric Analysis of Smart Growth Strategies in California

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Abstract

This paper by Chattopadhyay & Taylor (2012) examines the impact that urban form has on vehicle miles traveled (VMT) by using household-level survey data from the 2001 National Household Travel Survey (NHTS). By drawing on McFadden's hierarchical choice theory, they model residential location decisions as a structured process that influences travel demand. The study uses a three-stage least squares (3SLS) approach to address both endogeneity and multicollinearity, and this reveals that smart growth policies significantly reduce VMT. Some examples of these policies include higher residential density, increasing public transit investments, as well as improving the job-housing balance. A simulation of California itself suggests that increasing these urban form features by 10% could reduce VMT by up to 20%. Having these findings highlights the long-term effectiveness of land use policies in curbing transit-related gas emissions, which offers an alternative to fuel taxes. These results support integrating more smart growth strategies into regional planning to promote more sustainable urban development as well as reduce our current dependence on automobiles.

I. Pre-Estimation Questions

1. Role of Urban Form Features in Smart Growth Strategies

The term “smart growth” refers to land use policies aiming to reduce auto dependency by designing more urban centers that promote walking, biking, and public transit. Some aspects this focuses on are building more dense neighborhoods, improving the job-housing balance, as well as enhancing public transit. Having higher residential density would reduce the necessity of long commutes, as homes would be closer to essential services. Creating more job centers within these residential communities would also help shorten commute distances, as well as encourage other forms of transportation. Having more efficient and reliable public transit systems would also decrease the current reliance we have on personal vehicles, which would reduce vehicle miles traveled (VMT) and greenhouse gas (GHG) emissions.

Having these features directly addresses the policy issue by reducing transportation-related energy consumption. The study suggests that regions with higher densities and better transit infrastructure see a significant decrease in household VMT, which supports the success of California’s policies like SB 375 and AB 32 as well.

2. Residential Sorting (Self-Selection Issue)

Residential density and job-housing balance can be endogenous in a VMT demand model. This is due to people usually choosing where they live based on personal preferences and work locations. Having these factors also introduces a self-selection bias, such as households driving often choosing more suburban and low-density areas, while those who prefer a more car-free lifestyle would choose a transit-accessible and highly dense neighborhood. Since these choices are directly influenced by individual preference, the error term in the VMT model could

be correlated with the dependent variable (VMT) as well as the independent variables like urban form features. This makes it difficult to isolate the true causal impact of urban density on VMT.

3. Fuel Tax vs. Land Use Policies for Reducing VMT

Having both fuel taxes and land use policies could reduce VMT, but they differ in impact, feasibility, and most importantly the long-term effectiveness and impact.

Fuel tax could be more favorable for an immediate impact, as raising prices is a direct discouragement for excessive driving, and instead incentivizes carpooling or public transit more. It is also the easiest to administer since the taxes are straightforward to implement and collect. Having these taxes would also generate revenue, which can then be used to fund public transit improvements or infrastructure. However, arguments against include a regressive impact, since it would disproportionately affect lower-income households relying on driving. The tax is also a more short-term solution, as many people do not have a viable alternative, and relying on adapting behavior would take a long time. It is also very socially and politically looked down on, as fuel taxes are often faced with harsh resistance from the public and policymakers.

On the other side, land use policies could be better for long-term effectiveness, as creating denser communities and improving transit infrastructure would gradually and naturally reduce car dependency. It also encourages a more sustainable lifestyle, since walking, biking, and transit would become more convenient. It would also stimulate local economies, as investments in urban redevelopment and transit projects could also lead to the creation of new jobs. However, arguments would include its expense, as infrastructure development and urban rezoning both require substantial funding. It is also slow to implement, as it requires significant

planning and investment over a couple of decades. This also makes it difficult to monitor, as its success directly depends on effective urban planning and enforcement.

4. McFadden's Theory of Hierarchical Choice

Many studies currently rely on a single spatial unit, such as a census tract or zip code, for all urban-form features due to the convenience of readily available data. McFadden's theory explains how households make location choices more hierarchically. Households first select a metropolitan area meeting their broader needs, such as a job opportunity or public transit access. Within this chosen metro area, they then choose a location and county based on other factors, such as commuting convenience and job concentration. Within said selected country, they then pick a neighborhood or census tract based on local amenities, such as housing accessibility and density.

5. How McFadden's Theory Justifies a 3SLS Model

Using the Three-Stage Least Squares (3SLS) method would address two key econometric issues, these being endogeneity and multicollinearity. Households usually self-select where they live based on factors mentioned above, such as transit access and job locations, which makes urban form features endogenous. The 3SLS model resolves this endogeneity by incorporating instrumental variables to account for this self-selection, which then reduces bias. It recognizes that VMT and urban form decisions are not independent factors, but more simultaneous choices instead. For multicollinearity, many urban form features tend to move together, such as job density and transit access. The 3SLS model would separate these effects by structuring these urban form features at different spatial levels. For example, transit funding would be at the metro level, job density at the county level, and residential density would be at the neighborhood level.

Having these levels would prevent the urban form variables from being too closely correlated, which then improves the precision of the estimation.

6. Complete Theoretical Specification of the SLS Structural Demand Model

The study uses a simultaneous equations model for VMT demand, where the urban form features are treated as endogenous variables.

The Original Model

- $Q = f(p, I, x1, x2, x3) + \epsilon_1$
- $x1 = g1(z1) + \epsilon_2$
- $x2 = g2(x1, z2) + \epsilon_3$
- $x3 = g3(x2, z3) + \epsilon_4$

The Complete Modified Model

- $VMT_i = \beta_0 + \beta_1 Price_i + \beta_2 Income_i + \beta_3 ResDen_i + \beta_4 JobSpc_i + \beta_5 TransitPC_i + \epsilon_i$
- $ResDen_i = \gamma_0 + \gamma_1 JobSpc_i + \gamma_2 TransitPC_i + \gamma_3 Household\ Variables_i + \mu_i$
- $JobSpc_i = \delta_0 + \delta_1 TransitPC_i + \delta_2 Regional\ Variables_i + \eta_i$
- $TransitPC_i = \theta_0 + \theta_1 Regional\ Variables_i + \nu_i$

Key

- VMT: Vehicle miles traveled
- Price: Cost per mile of travel
- Income: Household income
- ResDen: Residential density at the census tract level

- JobSpc: Job density at the county level
- TransitPC: Public transit investment per capita at the metro level
- Household Variables: Such as household size, number of workers, etc.
- Regional Variables: Metro-specific factors
- ϵ, μ, η, v : Error terms capturing unobserved influences

7. Narrative Description of Dataset

The study uses data from three primary sources, these being the *2001 National Household Travel Survey* (NHTS), the *U.S. Census Bureau (2000 Census Data)*, as well as the *National Transit Database*. The *2001 NHTS* contains 7,696 households from the 18 major U.S. metropolitan areas and measures household traveling behavior including the annual VMT. It also includes socioeconomic characteristics, such as income, household composition, as well as car ownership. The *U.S. Census Bureau* provides demographic and economic data from the census tract level, such as residential density, value of homes, and the current job-housing balance. The third source, the *National Transit Database* reports transit operating expenses at the metropolitan level, which is then used to estimate the per capita public transit funding. The dataset is structured hierarchically, these being the metropolitan level, county level, and neighborhood level. The metropolitan level includes public transit investment in the MSA and CMSA areas, the county level contains job density and employment per capita, and the neighborhood level census tract includes residential density through housing units per square mile. Structuring the data at these multiple levels lets the study capture more geographic variation in both urban form and travel behavior.

2. Post-Estimation Questions

8. OLS Model Estimation and Interpretation

TABLE I
OLS Regression Results

Variable	Coefficient	Standard Error	t	P> t	95% Confidence Interval	
lprice	-1.672	0.139	-12.07	0.000	-1.944	-1.401
lresden	-0.270	0.022	-12.19	0.000	-0.313	-0.226
ljobspc	-0.332	0.104	-3.19	0.001	-0.535	-0.128
ltransitpc	-0.557	0.041	-13.46	0.000	-0.638	-0.476

The coefficient for the price (lprice) is -1.672, meaning that increasing the dollar cost per mile by 1% leads to a 1.672% decrease in VMT when everything else is held constant. This is negative elasticity, suggesting that households will drive less in response to rising driving costs from fuel prices, taxes, and/or fuel efficiency improvements.

For residential density (lresden), a 1% increase results in a 0.270% reduction in VMT as well. Having this higher density can be seen as improving access to amenities, jobs, as well as public transit, which can all reduce the reliance on personal vehicles. This value is much higher than previous studies by Bento et al. of 0.20 in 2003 and Brownstone et al. of 0.12 in 2009, which indicates that our sample has stronger urban density.

A 1% increase in job density (ljobspc) leads to a 0.332% decrease in VMT, which correlates with more concentrated employment centers directly shortening commute distances, as well as enhancing walkability and transit usage. This estimate is also significantly higher than Ewing et al. in 2010, where they reported a near-zero effect of job density on VMT.

For public transit, increasing 1% in public transit accessibility (*ltransitpc*) leads to a 0.557% decrease in VMT. Having this large negative elasticity points to the idea that having better public transit options is strongly reducing car dependency. This value shows how important investments in public transit can be as a policy tool for reducing VMT.

These OLS results demonstrate how price, residential density, job density, and transit accessibility all have the power to significantly reduce the vehicle miles traveled. Public transit accessibility has the strongest effect, which emphasizes the role of transit infrastructure when it comes to shaping travel behavior.

9. Impact of Multicollinearity on OLS Estimation

To assess the impact that multicollinearity has on the estimation of VMT, we use two different datasets. Dataset I has 5,474 observations, where the urban-form variables are all measured from the same spatial scale (census tract). This includes population density (*popden*), residential density (*resden*), as well as employment density (*empden*). Dataset II with 7,696 observations uses urban-form variables at a different hierarchical spatial scale. This includes residential density (*resden*) at the census tract, job density per capita (*jobspc*) at the county, and transit funding per capita (*transitpc*) at the metropolitan level.

Using Dataset I, there are high pairwise correlations among the urban-form variables:

$$r(\text{popden}, \text{resden}) = 0.889, r(\text{resden}, \text{empden}) = 0.751, \text{ and}$$

$r(\text{popden}, \text{empden}) = 0.602$. These are high correlations, suggesting the presence of multicollinearity that can distort elasticity estimates. In order to examine this, we can estimate seven different OLS models including different combinations of these variables.

TABLE II
Dataset I: Multicollinearity in Same Spatial Scale

Model Specification	Elasticity Estimates		
	<i>popden</i>	<i>resden</i>	<i>empden</i>
all three	-1.069	-0.408	1.437
<i>popden, resden</i>	-0.67	0.26	-
<i>resden, empden</i>	-	-1.29	0.92
<i>popden, empden</i>	-1.52	-	1.29
only <i>popden</i>	-0.45	-	-
only <i>resden</i>	-	-0.44	-
only <i>empden</i>	-	-	-0.27

When all three of the variables are included, the signs of the coefficients fluctuate from negative to positive. The estimates are all highly unstable as well, which confirms the issue of multicollinearity. When the variables are included individually, they retain their expected signs, but the magnitudes change drastically when combined.

TABLE III
Dataset II: Multicollinearity in Different Spatial Scale

Model Specification	Elasticity Estimates		
	<i>resden</i>	<i>jobspe</i>	<i>transitpc</i>
all three	-0.27	-0.33	-0.56
<i>resden, jobspe</i>	-0.29	0.36	-
<i>jobspe, transitpc</i>	-	-0.54	-0.59
<i>resden, transit pc</i>	-1.52	-	1.29
only <i>resden</i>	-0.30	-	-
only <i>jobspe</i>	-	-0.59	-
only <i>transitpc</i>	-	-	-0.60

When estimating the same set of models using Dataset II with urban-form variables being measured at different spatial levels, we see that there is no sign switching, and the elasticity estimates are relatively stable. This indicates that multicollinearity is not a major issue for this model. The elasticity estimates being consistent even with different specifications suggests that using urban-form variables from different spatial scales will improve the reliability of the estimates.

Overall, when urban-form variables are measured from the same spatial scale, there are high correlations that lead to multicollinearity and unstable elasticity estimates. When theta re measured from different spatial scales, multicollinearity is mitigated, which results in more stable and reliable estimates. Having this analysis shows how important choosing appropriate spatial scales is when modeling transportation demand in order to avoid estimation distortions.

10. Comparison of OLS and 3SLS Models

There is endogeneity and bias in the OLS model, as the Hausman test confirms there is endogeneity in resden, jobspc, and transitpc. The OLS estimates are biased and inconsistent, since it underestimates the effects of residential density and job space. This is likely due to omitting variables, as well as self-selection bias. The 3SLS model has improvements by accounting for this endogeneity by incorporating a system of equations with more precise estimates. The elasticity estimates for resden and jobspc increase significantly from -0.27 to -0.82 and -0.33 to -0.65 respectively, which suggests that the OLS model underestimates the effects they have on VMT. We can see that the elasticity of transitpc remains relatively stable, only going from -0.56 to -0.52 in OLS to 3SLS, which indicates lower bias for this variable only.

Interpreting the key variable of price, it is significant and retains the expected signs in both of the models, which suggests that fuel cost per mile does influence VMT. The residential density (resden) had a stronger negative effect in the 3SLS model, which indicates that employment density plays a crucial role when it comes to reducing VMT as well. The transit per capita (transitpc) also shows this with similar coefficients in both models, suggesting that public transit investment is a reliable tactic to reduce VMT.

11. Land Use Policy versus Fuel Tax Policy: Quantitative Impact Analysis

Although there is this key debate in transportation and urban planning for the effectiveness of land use policies versus fuel tax policies when reducing VMT, both meet in their aims of decreasing automobile dependence. Their differences are in the mechanisms, feasibility, as well as the long-term impact. Using the 3SLS model quantifies this effect of each policy.

In the full sample, the average household VMT is around ~22,182 miles per year. Having a 10% increase in urban form and land use policy measures results in:

- *resden increase of 234 people/square mile → 1,826 mile/year VMT reduction*
 - $- 0.822 \times 22182 \times 0.1$
- *jobspc increase of 0.045 jobs/person → 1,431 mile/year VMT reduction*
 - $- 0.515 \times 22182 \times 0.1$
- *transitpc increase of \$17,000/capita → 1,143 mile/year VMT reduction*
 - $- 0.645 \times 22182 \times 0.1$
- *combined impact of 4,400 mile/pear VMT reduction → ~20%*
 - $- 1.792 \times 22182 \times 0.1$

On the other hand, a fuel tax directly raises the cost per-mile of travel. The sample average cost per mile is 6.7 cents, and a 10% increase in cost per mile would lead to a reduction of 3,975 miles a year per household (~18%). These fuel tax policies have immediate impacts and effects, but have a history of facing high resistance due to market spillovers and consumer burden. There is also low political and social acceptability, and have the possibility of disproportionately impacting lower-income households. Land use policies may require a more long-term investment, but enhances community well being; Land use policies encourage a more gradual and lasting reduction in VMT through improving urban density, job accessibility, and public transit, making them more sustainable in the long term.

While land use policies may take longer time to implement, they are substantial in VMT reductions when done effectively. Fuel taxes do work faster, but are both politically and

economically difficult to implement. Combining the two by using both short-term fiscal tools with long-term urban planning would be the most effective path.

12. EXCEL Findings

The simulation results indicated that urban-form changes have the most substantial impact on reducing VMT, this being the most prominent for residential density and transit spending. For the Sacramento-Yolo Consolidated Metropolitan Statistical Area (SYCMSA), increasing residential density lead to a 29% reduction, while higher transit spending resulted in a 37% decrease alone. Combining the effects of all three changes resulted in a 55% reduction in VMT. There were similar trends for the Small Metropolitan Statistical Areas of California (SMSA), showing a higher 60% reduction. These reductions rely significantly on urban planning overhauls, which is difficult to implement due to constraints on an economic, social, and political scale. The findings do show that smart growth policies can effectively reduce auto dependence and emissions overtime if done effectively.

III. Conclusion

This study shows the significant role that urban form has in shaping travel behavior and reducing vehicle miles traveled (VMT). Econometric analysis using a three-stage least squares (3SLS) model showed that smart growth policies effectively lower automobile dependence, the most notable being increasing residential density, improving the job-housing balance, as well as expanding on public transit infrastructure. Fuel taxes provide an immediate but regressive impact, while land use policies provide a more sustainable and long-term solution. This is done by reshaping the already built environment to more naturally encourage alternative modes of transportation. Elasticity estimates also reinforce this idea that public transit investment and urban density play a crucial role in reducing VMT, which further supports policies like SB 375 in California. There should be further research done as well on how emerging transportation technologies and evolving land use patterns are interacting to further refine these policies to target more at reducing automobile dependence. Integrating these strategies into urban planning has the capacity to leading to more sustainable cities, lowering greenhouse gas emissions, as well as improving the overall quality of life.

References

Chattopadhyay, S., & Taylor, E. (2012). *Do Smart Growth Strategies Have a Role in Curbing Vehicle Miles Traveled? A Further Assessment Using Household Level Survey Data.* The B.E. Journal of Economic Analysis & Policy, 12(1), Article 37.

Appendix

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. use "C:\Users\923606369\Desktop\VMT-2001-Data-7696-Observations.dta", clear

. reg lvmt lprice lresden ljobspc ltransitpc lincome college nonwhite retired h
> hhchild16 hh2more numworker ownership
```

Source	SS	df	MS	Number of obs	=	7,696
Model	20827.7217	12	1735.64348	F(12, 7683)	=	319.13
Residual	41785.0976	7,683	5.43864345	Prob > F	=	0.0000
Total	62612.8193	7,695	8.13681862	R-squared	=	0.3326
				Adj R-squared	=	0.3316
				Root MSE	=	2.3321

lvmt	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
lprice	-1.672284	.1385849	-12.07	0.000	-1.943948 -1.40062
lresden	-.2698241	.0221271	-12.19	0.000	-.3131992 -.2264491
ljobspc	-.3315149	.1039349	-3.19	0.001	-.5352556 -.1277741
ltransitpc	-.5567217	.0413645	-13.46	0.000	-.6378074 -.4756361
lincome	.8783856	.0420183	20.90	0.000	.7960182 .960753
college	.2131809	.0620921	3.43	0.001	.0914635 .3348983
nonwhite	-.471254	.0664555	-7.09	0.000	-.6015248 -.3409831
retired	-.210969	.0833715	-2.53	0.011	-.3743998 -.0475381
hhchild16	.1846381	.0661242	2.79	0.005	.0550167 .3142595
hh2more	.986108	.0782328	12.60	0.000	.8327505 1.139466
numworker	.3545116	.0378257	9.37	0.000	.2803629 .4286603
ownership	1.073453	.0689547	15.57	0.000	.9382826 1.208623
_cons	-2.734728	.6240016	-4.38	0.000	-3.957942 -1.511515

```
. reg3 (lvm1 lprice lresden ljobspc ltransitpc linc college nonwhite retired hhchild16 h
> h2more numworker ownership) (lresden ljobspc boston dum nyc dum ladum phildum sac dum sfd
> um dc dum miamidum chic dum seattle portland phoenix atlanta lmedinc lmedhomevalue lavgh
> hsize) (ljobspc ltransitpc boston dum nyc dum ladum phildum sac dum sfd dum dc dum miamidum
> chic dum seattle portland phoenix atlanta) (ltransitpc boston dum nyc dum ladum phildum s
> ac dum sfd dum miamidum chic dum seattle portland phoenix atlanta)
```

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lvm1	7,696	12	2.431775	0.2731	3859.74	0.0000
lresden	7,696	17	2.777936	-3.6191	2437.40	0.0000
ljobspc	7,696	14	.6487251	-5.1157	1975.90	0.0000
ltransitpc	7,696	13	.1381646	0.9551	163685.37	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]
lvm1					
lprice	-1.792204	.1399182	-12.81	0.000	-2.066438 -1.517969
lresden	-.8229671	.0623386	-13.20	0.000	-.9451484 -.7007857
ljobspc	-.6452952	.2623104	-2.46	0.014	-1.159414 -.1311762
ltransitpc	-.5153162	.044916	-11.47	0.000	-.6033501 -.4272824
lincome	.8803591	.0426976	20.62	0.000	.7966734 .9640448
college	.2927211	.0645342	4.54	0.000	.1662365 .4192057
nonwhite	-.1671599	.0740026	-2.26	0.024	-.3122022 -.0221175
retired	-.1597376	.083786	-1.91	0.057	-.3239551 .00448
hhchild16	.1623101	.0676504	2.40	0.016	.0297178 .2949023
hh2more	.9041529	.0793239	11.40	0.000	.7486809 1.059625
numworker	.375528	.0380116	9.88	0.000	.3010266 .4500293
ownership	.7609274	.0791904	9.61	0.000	.605717 .9161377
_cons	.5731276	.7941829	0.72	0.471	-.9834422 2.129697
lresden					
ljobspc	11.63995	.4555629	25.55	0.000	10.74707 12.53284
boston dum	-1.984652	.1402381	-14.15	0.000	-2.259514 -1.709791
nyc dum	.5052916	.101059	5.00	0.000	.3072197 .7033636
ladum	.3790264	.1052036	3.60	0.000	.1728312 .5852216
phildum	-1.149391	.1354198	-8.49	0.000	-1.414809 -.8839728
sac dum	-1.034146	.1618822	-6.39	0.000	-1.351429 -.7168625
sfdum	-.9231629	.1272901	-7.25	0.000	-1.172647 -.6736789
dc dum	-1.06488	.1225694	-8.69	0.000	-1.305112 -.8246485
miamidum	-.2781693	.1502088	-1.85	0.064	-.5725733 .0162346
chic dum	-1.294314	.131334	-9.86	0.000	-1.551724 -1.036904
seattle	-1.688999	.1366217	-12.36	0.000	-1.956773 -1.421225
portland	-2.173547	.1637572	-13.27	0.000	-2.494506 -1.852589
phoenix	-1.327588	.1500378	-8.85	0.000	-1.621657 -1.03352
atlanta	-2.542386	.157832	-16.11	0.000	-2.851731 -2.233041
lmedinc	-1.293677	.0523579	-24.71	0.000	-1.396297 -1.191058
lmedhomevalue	-.6099546	.0701027	-8.70	0.000	-.7473534 -.4725558
lavghhsize	.6980439	.16692	4.18	0.000	.3708868 1.025201
_cons	38.53521	1.072616	35.93	0.000	36.43292 40.6375
ljobspc					
ltransitpc	4.446247	.1061495	41.89	0.000	4.238198 4.654296
boston dum	-6.335883	.1587663	-39.91	0.000	-6.64706 -6.024707

nycdum	-9.547966	.2302349	-41.47	0.000	-9.999219	-9.096714
ladum	-3.374397	.0847875	-39.80	0.000	-3.540578	-3.208217
phildum	-5.394217	.1345716	-40.08	0.000	-5.657972	-5.130461
sacdum	-1.303521	.0487971	-26.71	0.000	-1.399162	-1.207881
sfdum	-7.388836	.1831889	-40.33	0.000	-7.747879	-7.029792
dcdum	-6.111297	.1512113	-40.42	0.000	-6.407665	-5.814928
miamidum	-3.671878	.0951718	-38.58	0.000	-3.858411	-3.485344
chicdum	-5.970698	.1486982	-40.15	0.000	-6.262141	-5.679255
seattle	-6.844351	.1699257	-40.28	0.000	-7.177399	-6.511303
portland	-4.923928	.1263889	-38.96	0.000	-5.171646	-4.67621
phoenix	.0554775	.0303154	1.83	0.067	-.0039397	.1148947
atlanta	-3.571244	.0946318	-37.74	0.000	-3.756719	-3.385769
_cons	-17.31006	.391224	-44.25	0.000	-18.07685	-16.54328
<hr/>						
ltransitpc						
bostondum	1.473332	.0091567	160.90	0.000	1.455385	1.491279
nycdum	2.158198	.0076523	282.03	0.000	2.143199	2.173196
ladum	.7651122	.0079712	95.98	0.000	.7494889	.7807356
phildum	1.24149	.0092487	134.23	0.000	1.223362	1.259617
sacdum	.3187926	.0119883	26.59	0.000	.295296	.3422892
sfdum	1.705581	.0088223	193.33	0.000	1.688289	1.722872
dcdum	1.403371	.0086896	161.50	0.000	1.38634	1.420402
miamidum	.8404654	.0111851	75.14	0.000	.818543	.8623878
chicdum	1.378969	.0085794	160.73	0.000	1.362153	1.395784
seattle	1.576587	.0096099	164.06	0.000	1.557752	1.595423
portland	1.147153	.0113374	101.18	0.000	1.124932	1.169373
phoenix	.0178593	.0103404	1.73	0.084	-.0024076	.0381262
atlanta	.8472299	.0101724	83.29	0.000	.8272924	.8671675
<hr/>						
_cons	3.682097	.006792	542.12	0.000	3.668785	3.695409

Endogenous variables: lvmt lresden ljobspc ltransitpc

Exogenous variables: lprice lincome college nonwhite retired hhchild16
 hh2more numworker ownership bostondum nycdum ladum phildum sacdum sfdum
 dcdum miamidum chicdum seattle portland phoenix atlanta lmedinc
 lmedhomevalue lavghhsiz

```
. reg3 (lvmt lprice lresden ljobspc ltransitpc lincome college nonwhite retired hhchild16
> 6 hh2more numworker ownership) (lresden ljobspc bostondum nycdum ladum phildum sacdum
> sfdum dcdum miamidum chicdum seattle portland phoenix atlanta lmedinc lmedhomevalue la
> vghhsiz) (ljobspc ltransitpc bostondum nycdum ladum phildum sacdum sfdum dcdum miamid
> um chicdum seattle portland phoenix atlanta) (ltransitpc bostondum nycdum ladum phildu
> m sacdum sfdum dcdum miamidum chicdum seattle portland phoenix atlanta)
```

Three-stage least-squares regression

Equation	Obs	Parms	RMSE	"R-sq"	chi2	P
lvmt	7,696	12	2.431775	0.2731	3859.74	0.0000
lresden	7,696	17	2.777936	-3.6191	2437.40	0.0000
ljobspc	7,696	14	.6487251	-5.1157	1975.90	0.0000
ltransitpc	7,696	13	.1381646	0.9551	163685.37	0.0000

	Coef.	Std. Err.	z	P> z	[95% Conf. Interval]

lvmt						
lprice	-1.792204	.1399182	-12.81	0.000	-2.066438	-1.517969
lresden	-.8229671	.0623386	-13.20	0.000	-.9451484	-.7007857
ljobspc	-.6452952	.2623104	-2.46	0.014	-1.159414	-.1311762
ltransitpc	-.5153162	.044916	-11.47	0.000	-.6033501	-.4272824
lincome	.8803591	.0426976	20.62	0.000	.7966734	.9640448
college	.2927211	.0645342	4.54	0.000	.1662365	.4192057
nonwhite	-.1671599	.0740026	-2.26	0.024	-.3122022	-.0221175
retired	-.1597376	.083786	-1.91	0.057	-.3239551	.00448
hhchild16	.1623101	.0676504	2.40	0.016	.0297178	.2949023
hh2more	.9041529	.0793239	11.40	0.000	.7486809	1.059625
numworker	.375528	.0380116	9.88	0.000	.3010266	.4500293
ownership	.7609274	.0791904	9.61	0.000	.605717	.9161377
_cons	.5731276	.7941829	0.72	0.471	-.9834422	2.129697
 lresden						
ljobspc	11.63995	.4555629	25.55	0.000	10.74707	12.53284
bostondum	-1.984652	.1402381	-14.15	0.000	-2.259514	-1.709791
nycdum	.5052916	.101059	5.00	0.000	.3072197	.7033636
ladum	.3790264	.1052036	3.60	0.000	.1728312	.5852216
phildum	-1.149391	.1354198	-8.49	0.000	-1.414809	-.8839728
sacdum	-1.034146	.1618822	-6.39	0.000	-1.351429	-.7168625
sfdum	-.9231629	.1272901	-7.25	0.000	-1.172647	-.6736789
dcdum	-1.06488	.1225694	-8.69	0.000	-1.305112	-.8246485
miamidum	-.2781693	.1502088	-1.85	0.064	-.5725733	.0162346
chicdum	-1.294314	.131334	-9.86	0.000	-1.551724	-1.036904
seattle	-1.688999	.1366217	-12.36	0.000	-1.956773	-1.421225
portland	-2.173547	.1637572	-13.27	0.000	-2.494506	-1.852589
phoenix	-1.327588	.1500378	-8.85	0.000	-1.621657	-1.03352
 atlanta	-2.542386	.157832	-16.11	0.000	-2.851731	-2.233041
lmedinc	-1.293677	.0523579	-24.71	0.000	-1.396297	-1.191058
lmedhomevalue	-.6099546	.0701027	-8.70	0.000	-.7473534	-.4725558
lavghhsiz	.6980439	.16692	4.18	0.000	.3708868	1.025201
_cons	38.53521	1.072616	35.93	0.000	36.43292	40.6375
 ljobspc						
ltransitpc	4.446247	.1061495	41.89	0.000	4.238198	4.654296
bostondum	-6.335883	.1587663	-39.91	0.000	-6.64706	-6.024707
nycdum	-9.547966	.2302349	-41.47	0.000	-9.999219	-9.096714
ladum	-3.374397	.0847875	-39.80	0.000	-3.540578	-3.208217
phildum	-5.394217	.1345716	-40.08	0.000	-5.657972	-5.130461
sacdum	-1.303521	.0487971	-26.71	0.000	-1.399162	-1.207881
sfdum	-7.388836	.1831889	-40.33	0.000	-7.747879	-7.029792
dcdum	-6.111297	.1512113	-40.42	0.000	-6.407665	-5.814928
miamidum	-3.671878	.0951718	-38.58	0.000	-3.858411	-3.485344
chicdum	-5.970698	.1486982	-40.15	0.000	-6.262141	-5.679255
seattle	-6.844351	.1699257	-40.28	0.000	-7.177399	-6.511303
portland	-4.923928	.1263889	-38.96	0.000	-5.171646	-4.67621
phoenix	.0554775	.0303154	1.83	0.067	-.0039397	.1148947
atlanta	-3.571244	.0946318	-37.74	0.000	-3.756719	-3.385769
_cons	-17.31006	.391224	-44.25	0.000	-18.07685	-16.54328
 ltransitpc						
bostondum	1.473332	.0091567	160.90	0.000	1.455385	1.491279
nycdum	2.158198	.0076523	282.03	0.000	2.143199	2.173196
ladum	.7651122	.0079712	95.98	0.000	.7494889	.7807356
phildum	1.24149	.0092487	134.23	0.000	1.223362	1.259617
sacdum	.3187926	.0119883	26.59	0.000	.295296	.3422892

sfdum	1.705581	.0088223	193.33	0.000	1.688289	1.722872
dcdum	1.403371	.0086896	161.50	0.000	1.38634	1.420402
miamidum	.8404654	.0111851	75.14	0.000	.818543	.8623878
chicdum	1.378969	.0085794	160.73	0.000	1.362153	1.395784
seattle	1.576587	.0096099	164.06	0.000	1.557752	1.595423
portland	1.147153	.0113374	101.18	0.000	1.124932	1.169373
phoenix	.0178593	.0103404	1.73	0.084	-.0024076	.0381262
atlanta	.8472299	.0101724	83.29	0.000	.8272924	.8671675
_cons	3.682097	.006792	542.12	0.000	3.668785	3.695409

Endogenous variables: lvmt lresden ljobspc ltransitpc
 Exogenous variables: lprice lincome college nonwhite retired hhchild16
 hh2more numworker ownership bostondum nycdum ladum phildum sacdum sfdum
 dcdum miamidum chicdum seattle portland phoenix atlanta lmedinc
 lmedhomevalue lavghhsize

```
.
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.

. use "C:\Users\923606369\Desktop\VMT-2001-data-5474-Observations.
> dta", clear

. reg lvmt lprice lresdt lempdt lpopdt linc college nonwhite retir
> ed children hh2more numworker ownership
```

Source	SS	df	MS	Number of obs
> = 5,474				F(12, 5461)
> = 243.22				
Model	16666.8902	12	1388.90752	Prob > F
> = 0.0000				
Residual	31185.5148	5,461	5.71058686	R-squared
> = 0.3483				Adj R-squared
> = 0.3469				
Total	47852.4051	5,473	8.74335923	Root MSE
> = 2.3897				
<hr/>				
> -	lvmt	Coef.	Std. Err.	t P> t [95% Con
> f. Interval]				
<hr/>				

	lprice	-1.068835	.175006	-6.11	0.000	-1.411916
>	-.7257534					
>	lresdt	-.4083854	.0845368	-4.83	0.000	-.5741113
>	-.2426595					
>	lempdt	1.43655	.0738903	19.44	0.000	1.291696
>	1.581405					
>	lpopdt	-1.289436	.0766124	-16.83	0.000	-1.439627
>	-1.139245					
>	lincome	1.031437	.0504734	20.44	0.000	.9324886
>	1.130385					
>	college	.1682157	.0754665	2.23	0.026	.0202713
>	.3161602					
>	nonwhite	-.4332954	.0772458	-5.61	0.000	-.584728
>	-.2818628					
>	retired	-.7904719	.1179462	-6.70	0.000	-1.021693
>	-.5592504					
>	children	.0090244	.0440977	0.20	0.838	-.0774246
>	.0954734					
>	hh2more	.5071239	.1053995	4.81	0.000	.3004989
>	.7137488					
>	numworker	.2325593	.0526022	4.42	0.000	.1294381
>	.3356805					
>	ownership	-.0885329	.0183993	-4.81	0.000	-.1246029
>	-.0524629					
>	_cons	-2.28435	.7647191	-2.99	0.003	-3.783504
>	-.7851957					

```
. reg lvmt lprice lresdt lempdt lpopdt lincome college nonwhite re
> tired children hh2more numworker ownership
```

Source	SS	df	MS	Number of obs		
> = 5,474				F(12, 5461)		
> = 243.22						
> Model	16666.8902	12	1388.90752	Prob > F		
> = 0.0000						
> Residual	31185.5148	5,461	5.71058686	R-squared		
> = 0.3483				Adj R-squared		
> = 0.3469						
> Total	47852.4051	5,473	8.74335923	Root MSE		
> = 2.3897						
<hr/>						
> f. Interval]	lvmt	Coef.	Std. Err.	t	P> t	[95% Con
> f. Interval]						
>	lprice	-1.068835	.175006	-6.11	0.000	-1.411916
>	-.7257534					
>	lresdt	-.4083854	.0845368	-4.83	0.000	-.5741113
>	-.2426595					

	lempdt	1.43655	.0738903	19.44	0.000	1.291696
>	1.581405					
>	lpopdt	-1.289436	.0766124	-16.83	0.000	-1.439627
>	-1.139245					
>	lincome	1.031437	.0504734	20.44	0.000	.9324886
>	1.130385					
>	college	.1682157	.0754665	2.23	0.026	.0202713
>	.3161602					
>	nonwhite	-.4332954	.0772458	-5.61	0.000	-.584728
>	-.2818628					
>	retired	-.7904719	.1179462	-6.70	0.000	-1.021693
>	-.5592504					
>	children	.0090244	.0440977	0.20	0.838	-.0774246
>	.0954734					
>	hh2more	.5071239	.1053995	4.81	0.000	.3004989
>	.7137488					
>	numworker	.2325593	.0526022	4.42	0.000	.1294381
>	.3356805					
>	ownership	-.0885329	.0183993	-4.81	0.000	-.1246029
>	-.0524629					
>	_cons	-2.28435	.7647191	-2.99	0.003	-3.783504
>	-.7851957					

> -----

```
. cor popdt resdt empdpt
(obs=5, 474)
```

	popdt	resdt	empdt
popdt	1.0000		
resdt	0.8885	1.0000	
empdt	0.6024	0.7508	1.0000

multiply coefficient by log							10% increase calculations																		
Final model with three endog variables and all hh exog variables as instruments: OWN (SFO and LA)																									
SFO/LA			OWN VALUES			SACRAMENTO: OWN VALUES			SMALL MSA: OWN VALUES			SACRAMENTO: LA/SFO			Small MSA										
Coeff.	Value	log	Sacramento	log	Sacramento	Iprice	Coeff.	Value	Small MSA	log	Small MSA	Coef.	Value	Avg. VMT	Down										
Iprice	-1.7922	0.0705	-2.65214	4.753181	Iprice	-1.7922	0.070328	-2.65458	4.757551	Iprice	-1.7922	-2.65315	4.722729	resden	-0.82297	22182	-1825.51								
Iresden	-0.82297	2769.374	7.926377	-6.52315	Iresden	-0.82297	1804.259	7.512211	-4.23233	Iresden	-0.82297	1917.151	-2.59616	transitpc	0.51532	22182	-1143.07								
Ijob	-0.6453	0.43758	-0.8265	0.533333	Ijob	-0.6453	0.440964	-0.81879	0.528362	Ijob	-0.6453	0.391596	0.93753	jobspsc	-0.6453	22182	-1431.39								
Iran	-0.51532	132.9291	4.889816	-2.5198	Iran	-0.51532	54.62	0.02644	-2.06147	Iran	-0.51532	45.87349	3.825887	price	-1.7922	22182	-3975.47								
Iinc	0.880359	62101.17	11.03652	9.716101	Iinc	0.880359	62960.89	11.05027	9.728205	Iinc	0.880359	52975.67	8.87759	9.576184											
college	0.292721	0.73006	-0.31462	-0.09209	college	0.292721	0.707692	-0.34575	-0.102121	college	0.292721	0.687651	-0.37447												
nonwhite	-0.16716	0.357945	0.17238	0.171736	nonwhite	-0.16716	0.230769	-1.466375	0.245113	nonwhite	-0.16716	0.312349	-1.16364	0.194513											
retired	-0.15974	0.232657	-1.44279	0.230468	retired	-0.15974	0.241026	-1.42285	0.227283	retired	-0.15974	0.230024	-1.46957	0.234746											
hh16	0.16231	0.338453	-1.08337	-0.17584	hh16	0.16231	0.34359	-1.06831	-0.1734	hh16	0.16231	0.382567	-0.96085	-0.15596											
hh2	0.904153	0.779909	0.24858	-0.22475	hh2	0.904153	0.8	0.22314	-0.20176	hh2	0.904153	0.813559	0.20634	-0.18656											
numwork	0.375528	1.374483	0.318078	0.119447	numwork	0.375528	1.405128	0.340128	0.127728	numwork	0.375528	1.353511	0.302702	0.113673											
home	0.760927	0.674542	-0.39372	-0.29959	home	0.760927	0.758974	-0.27579	-0.20985	home	0.760927	0.704601	-0.35012	-0.26642											
cons	0.573128	1	0.573128	cons	0.573128	1	0.573128	cons	0.573128	1	0.573128	cons	0.573128	1	0.573128										
	6.262163	524.3518				7.257381	1418.537				7.109368	1223.374													
	*sum			^vmt prediction			*sum			^vmt prediction			*sum			^vmt prediction									
endog = Iresden, Ijob, Iran																									
Final model with three endog variable and all hh exog variables as instruments: TRANSFER, all three urban features replaced							SMALL MSA: TRANSFER																		
SFO/LA			Sacramento			log			Sacramento			log			Small MSA										
Coeff.	Value	log	Sacramento	log	Sacramento	Iprice	Coeff.	Value	Small MSA	log	Small MSA	Coef.	Value	Avg. VMT	Down										
Iprice	-1.7922	0.0705	-2.65214	4.753181	Iprice	-1.7922	0.070328	-2.65458	4.757551	Iprice	-1.7922	0.071708	-2.65315	4.722729	resden	-0.82297	22182	-1825.51							
Iresden	-0.82297	2769.374	7.926377	-6.52315	Iresden	-0.82297	2769.374	7.926377	-6.52315	Iresden	-0.82297	2769.374	7.926377	-6.52315	transitpc	0.51532	22182	-1143.07							
Ijob	-0.6453	0.43758	-0.8265	0.533333	Ijob	-0.6453	0.43758	-0.8265	0.533333	Ijob	-0.6453	0.43758	-0.8265	0.533333	jobspsc	-0.6453	22182	-1431.39							
Iran	-0.51532	132.9291	4.889816	-2.5198	Iran	-0.51532	132.9291	4.889816	-2.5198	Iran	-0.51532	132.9291	4.889816	-2.5198	price	-1.7922	22182	-3975.47							
Iinc	0.880359	62101.17	11.03652	9.716101	Iinc	0.880359	62960.89	11.05027	9.728205	Iinc	0.880359	52975.67	8.87759	9.576184											
college	0.292721	0.73006	-0.31462	-0.09209	college	0.292721	0.707692	-0.34575	-0.102121	college	0.292721	0.687651	-0.37447												
nonwhite	0.16716	0.357945	-1.07738	0.171736	nonwhite	0.16716	0.230769	-1.44544	0.245113	nonwhite	0.16716	0.312349	-1.16364	0.194513											
retired	-0.15974	0.232657	-1.44279	0.230468	retired	-0.15974	0.241026	-1.42285	0.227283	retired	-0.15974	0.230024	-1.46957	0.234746											
hh16	0.16231	0.338453	-1.08337	-0.17584	hh16	0.16231	0.34359	-1.06831	-0.1734	hh16	0.16231	0.382567	0.96085	-0.15596											
hh2	0.904153	0.779909	0.24858	-0.22475	hh2	0.904153	0.8	0.22314	-0.20176	hh2	0.904153	0.813559	0.20634	-0.18656											
numwork	0.375528	1.374483	0.318078	0.119447	numwork	0.375528	1.405128	0.340128	0.127728	numwork	0.375528	1.353511	0.302702	0.113673											
home	0.760927	0.674542	-0.39372	-0.29959	home	0.760927	0.758974	-0.27579	-0.20985	home	0.760927	0.704601	-0.35012	-0.26642											
cons	0.573128	1	0.573128	cons	0.573128	1	0.573128	cons	0.573128	1	0.573128	cons	0.573128	1	0.573128										
	6.262163	524.3518				6.463177	641.0948				6.186806	486.2903													
	*sum			^vmt prediction			0.451941 =L3/L21			0.397499 =R43/R21															
				0.548059 =L4-L44			0.602501 =L44			0.397499 =R43/R21															
				^percent down			^percent down			^percent down															