TRIMMS User Manual
Version 3.0

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Table of Contents

List of Tables iv
List of Figures iv
1. Introduction 1
1.1 About TRIMMS 1
1.2 New or Updated Features of Version 3.0 2
1.2.1 New Interface 2
1.2.2 Comprehensive Emission Analysis 2
1.2.3 Land Use Impacts 3
1.2.4 User Manual 3
2. Using TRIMMS 5
2.1 Enabling Excel Macros and Starting TRIMMS 5
2.2 Navigating the Toolbar 7
3. Analysis Worksheet 8
3.1 Analysis Details 9
3.2 Employer-Based Commuter Programs 11
3.3 Strategies Affecting Travel Costs and Travel Times 12
3.4 Land Use Controls 13
4. Results Worksheet 14
4.1 Baseline and Final Travel Behavior 16
4.2 Changes in Social Costs 16
4.2.1 Changes in Air Pollution Emissions Costs 17
4.2.2 Changes in Congestion Costs 17
4.2.3 Changes in Excess Fuel Consumption Costs 17
4.2.4 Changes in Global Climate Change Costs 18
4.2.5 Changes in Health and Safety Costs 18
4.2.6 Changes in Noise Pollution Costs 18
4.3 Program Cost Effectiveness 18
4.3.1 Benefit to Cost Ratio Estimation 18
4.3.2 Sensitivity Analysis 19
4.4 Emission Analysis 22

5. TRIMMS Default Data 23
5.1 Global Parameters 23
5.1.1 Number of Working Days 24
5.1.2 U.S. Median Household Income and Population Density 24
5.1.3 Consumer Price Index 24
5.1.4 Discount Rate 24
5.1.5 Marginal Added Delay 25
5.1.6 Fuel Prices and Fuel Economy 25
5.1.7 Sensitivity Analysis Parameters 25
5.1.8 Social Costs 25
5.2 Regional Parameters 27
5.2.1 Baseline Travel Behavior Data 27
5.2.2 Population Density 27
5.2.3 Household Income 27
5.2.4 Industry Employment and Wages 27
5.2.5 Accident Rates 28
5.3 Social Costs 28
5.3.1 Congestion Costs 28
5.3.2 Health and Safety 29
5.3.3 Air Pollution 31
5.3.4 Global Climate Change 32
5.3.5 Noise Pollution 33
5.4 Elasticity Parameters 34
5.4.1 Fare and Trip Cost Elasticities 35
5.4.2 Parking Demand Elasticities 37
5.4.3 Land Use Control Elasticities 38
References 40
Appendices 45
A1. Constant Elasticity of Substitution Trip Demand Functions 46
A2. Program Support Evaluation 48
A3. Land Use Controls and Transit Travel Behavior 50
A4. Data Sources 20

List of Tables

Table 1 Monetary and Nonmonetary Accident Costs ($/occurrence, 2002 dollars) 30
Table 2 Noise Pollution Costs 34
Table 3 Fare and Price Elasticities 36
Table 4 Travel Time Elasticities 37
Table 5 Parking Pricing Elasticities 38
Table 6 Land-Use Elasticity (Concas and DeSalvo, 2008) 39

List of Figures

Figure 1 TRIMMS and Microsoft Excel Ribbon Toolbar 2
Figure 2 TRIMMS Model 4
Figure 3 Accessing Excel Trust Center 5
Figure 4 Customizing Macro Settings 6
Figure 5 Macro Warning: Excel 2007 7
Figure 6 TRIMMS Toolbar 8
Figure 7 Analysis Worksheet 9
Figure 8 Site-Specific Analysis Industry Sector Options 10
Figure 9 Area-Wide Analysis Industry Sector Options 11
Figure 10 Employer-Based Commuter Programs Evaluation 12
Figure 11 Strategies Affecting Travel Costs and Travel Times 13
Figure 12 Land Use Controls Evaluation 14
Figure 13 Running the Analysis 15
Figure 14 Worksheet Results 15
Figure 15 Change in Travel Behavior (Final Estimates vs. Baseline Data) 16
Figure 16 Impact on SOV Travel and in Social Costs 17
Figure 17 Net Program Benefits and Benefit-to-Cost Ratio 19
Figure 18 Sensitivity Analysis Button 20
Figure 19 Sensitivity Analysis Results 21
Figure 20 Emission Analysis Worksheet 23
Figure 21 Parameters Worksheet 26
Figure 22 Accessing the Elasticity Parameters 35

1. Introduction

This User Manual is directed to instruct users to start up TRIMMS Version 3.0, customize input parameters, and evaluate the costs and benefits of a wide range of transportation demand management initiatives. To guide users through the model, this manual follows a generic analysis example, modeling the implementation of a transit fare subsidy.

1.1 About TRIMMS

TRIMMS (Trip Reduction Impacts of Mobility Management Strategies) was developed by the National Center for Transit Research and the Center for Urban Transportation Research at the University of South Florida under a grant from the Florida Department of Transportation and the US Department of Transportation [1, 2]. TRIMMS is a visual basic (VB) application spreadsheet model that estimates the impacts of a broad range of transportation demand initiatives and provides program cost effectiveness assessment, such as net program benefit and benefit-to-cost ratio analysis.

TRIMMS evaluates strategies directly affecting the cost of travel, like public transportation subsidies, parking pricing, pay-as-you-go pricing, and other financial incentives. Subsidies are provided to the employee by the employer to reduce the costs associated with the use of a particular method of commuting. Subsidies can take different forms such as cash, discount passes, and vouchers.

TRIMMS also evaluates the impact of strategies affecting access and travel times and a host of employer-based program support strategies, such as: TDM program support initiatives, alternative work schedules, telework and flexible work hours, and worksite amenities.

TDM program support includes rideshare matching services, the provision of guaranteed ride home or emergency ride home for vanpool and carpool users; vanpool formation support; program promotion; and employee transportation coordinators. Alternative work schedules include compressed work week, flexible working hours, and telecommuting. Worksite amenities include the provision of childcare facilities and the presence of sidewalks connecting transit stops within or nearby the worksite.

Finally, this version of TRIMMS allows estimating the impact of land-use controls on transit patronage levels. These strategies include land-use policy changes affecting gross population density and retail establishment density levels, transit station accessibility improvements, and transit-oriented development initiatives. The approach to estimate changes in transit demand levels is based on constant-elasticity demand functions, as detailed below. More details about the evaluation of land-use controls are reported in Appendix A3.

TRIMMS predicts mode share and VMT changes brought about by the above TDM initiatives using constant elasticity of substitution (CES) trip demand functions. These functions estimate changes from baseline trip demands taking into account users' responsiveness to changes in pricing and travel times. The evaluation of program support strategies is based on regression equation coefficients that weight in the relative strength of program support strategies and pricing strategies. Appendix A1 details the modeling technique and the use of these demand functions.

Figure 2 shows TRIMMS' structure. Starting from a baseline scenario describing a TDM program in terms of commuter travel behavior (mode shares, average trip lengths, peak and off-peak spreads), TRIMMS evaluates the impacts of TDM implementation by estimating changes in travel behavior (mode shares, VMT reductions). Changes in the baseline scenario are then used to estimate changes in the external costs associated with these travel behavior changes.

Generally, costs that directly affect transportation users are defined as *internal costs* and those costs that do not directly affect these users are defined as *external costs*. External or societal costs belong to what economists describe as *negative externalities*. Negative externalities arise whenever costs associated with single occupant vehicle (SOV) use, such as added congestion delay, air pollution, and increased accident risk, are not directly sustained by auto users but are rather imposed on the society as a whole. TRIMMS estimates changes in costs for the following externalities:

- Air pollution emissions.
- Added congestion.
- Excess fuel consumption.
- Global climate change.
- Health and safety.
- Noise pollution.

1.2 New or Updated Features of Version 3.0

In response to TRIMMS Version 2.0 users' comments, TRIMMS presents significant upgrades, including a new interface, updated default parameters for 99 U.S. metropolitan statistical areas (MSAs), a wider range of emission pollutants, and a new module which allows estimating the impact of land-use controls on transit patronage levels.

1.2.1 New Interface

The new interface is intended to reduce the number of steps required to conduct the analysis, customize the data and update the analysis results. The upgrade relies on Microsoft Office ribbon interface (Figure 1). Upon starting TRIMMS, a custom toolbar in loaded into Excel Ribbon. The ribbon interface eliminates the need to use icon-based buttons in the worksheets, a feature of the previous version.

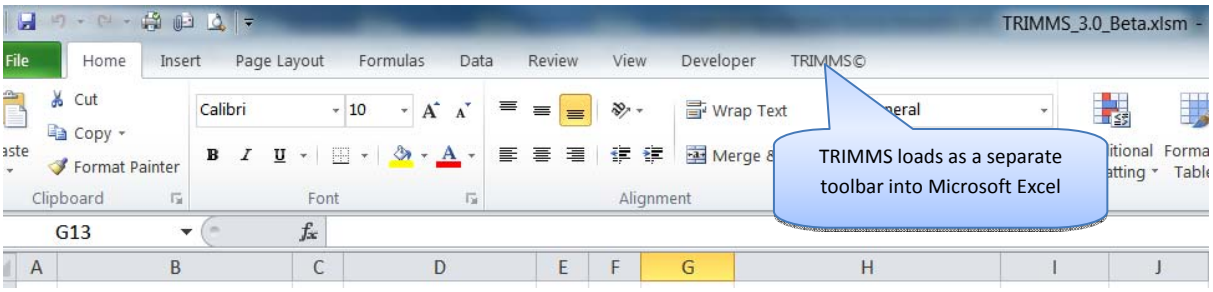


Figure 1 TRIMMS and Microsoft Excel Ribbon Toolbar

1.2.2 Comprehensive Emission Analysis

TRIMMS now evaluates the impact of a wide range of air pollution emissions. It uses default emission data from the Environmental Protection Agency Motor Vehicle Emission Simulator (MOVES) [3]. TRIMMS is loaded with

default exhaust tailpipe emission rates for each of the U.S. 99 MSAs at the combined county level. The estimates come from the MOVES2010a inventory at the combined county level for weekday peak and off-peak periods. MOVES 2010 replaced the previous emissions model, MOBILE 6.2 and can be used to conduct emission analysis to meet transportation planning and conformity requirements [4]. TRIMMS evaluates the following air pollution emissions:

- Ammonia (NH_3)
- Atmospheric Carbon Dioxide (CO_2)
- Carbon Monoxide (CO)
- CO_2 Equivalent
- Methane (CH_4)
- Nitrogen Dioxide (NO_2)
- Nitrogen Oxide (NO)
- Nitrous Oxide (N_2O)
- Oxides of Nitrogen (NOx)
- Particulate Matter (PM10) Sulfate Particulate
- PM10 Total and Sulfate Particulate
- PM2.5 Total
- Sulfur Dioxide (SO_2)
- Total Gaseous Hydrocarbons (HC)
- Volatile Organic Compounds (VOCs)

Note that this disaggregation also allows estimating the impact of reduction in ozone levels, as ground-level ozone exhaust emissions are produced by the chemical reaction of NOx and VOCs. More details about the emission inventory and data customization are provided in Section 4.4 of this manual.

1.2.3 Land Use Impacts

In addition to the broad range of TDM strategies discussed above, this version of TRIMMS allows estimating the impact of land-use controls on transit ridership levels. These strategies include land-use policy changes affecting gross population density and retail establishment density levels, transit station accessibility improvements, and transit-oriented development initiatives. The approach to estimate changes in transit demand levels is based on constant-elasticity demand functions, as detailed below. Appendix A3 of the user manual provides more details about the evaluation of land-use.

1.2.4 User Manual

This new version of TRIMMS comes with a separate user manual providing step-by-step instructions on the model's use and customization. The manual also provides detailed explanations on the model calculations, input data, and sources where obtain them. The model and user manual are compressed into a single data file that can be downloaded by accessing TRIMMS's standalone website at www.trimms.com. For support and enquiries, users can contact support@trimms.com.

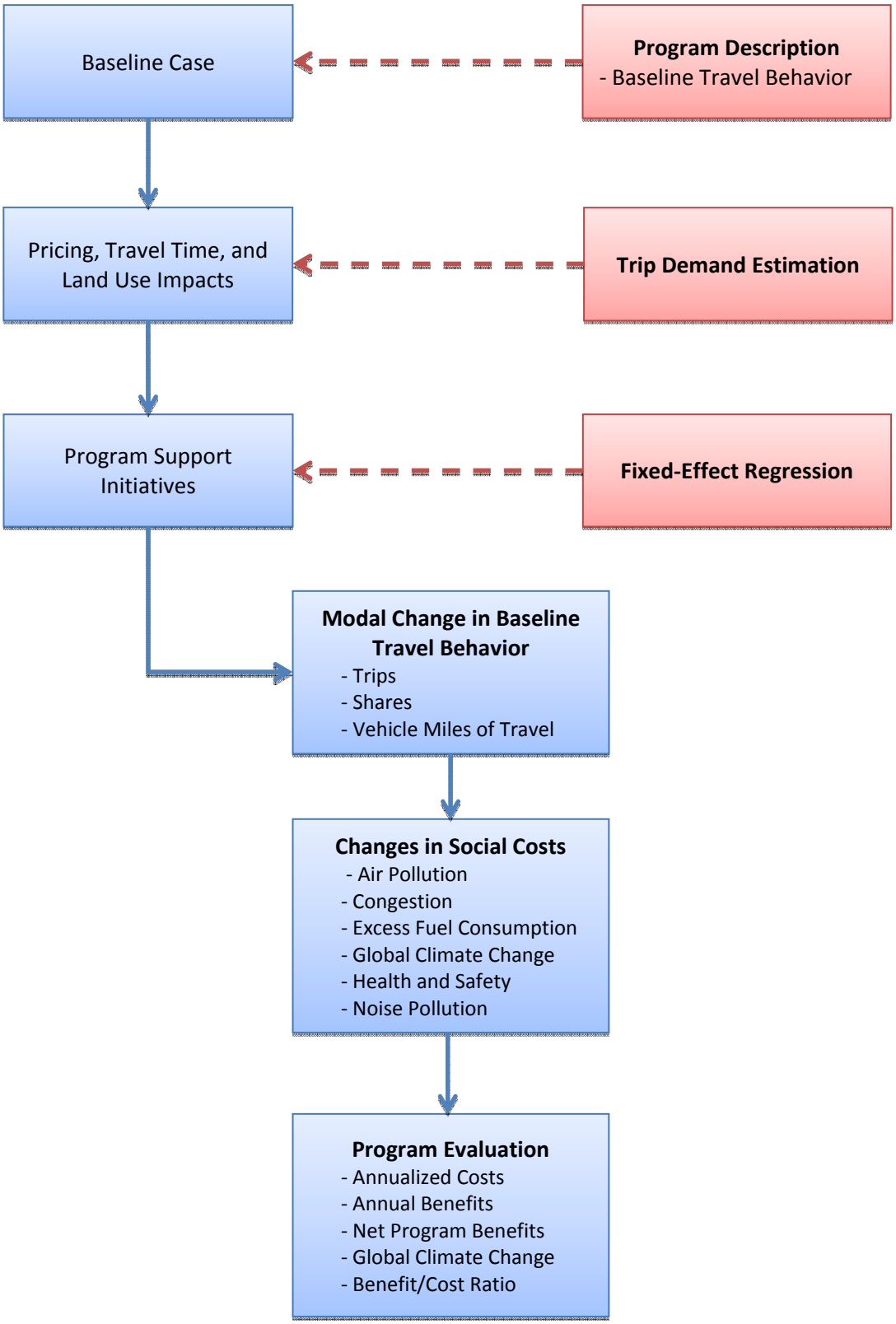


Figure 2 TRIMMS Model

2. Using TRIMMS

TRIMMS runs as a macro on the Microsoft Excel® software platform. Note that this version of TRIMMS only works with Microsoft Excel 2007 and 2010 versions, since it relies on the new Microsoft Office Ribbon interface. TRIMMS is based on a set of macros written in Visual Basic language that allow performing the sequence of steps showed in Figure 2.

2.1 Enabling Excel Macros and Starting TRIMMS

To run TRIMMS, Excel's security settings must be set to enable macros. The macro security settings are located in the Trust Center. In Excel 2007-2010 these are accessed by clicking on File → Options → Trust Center (Figure 3).

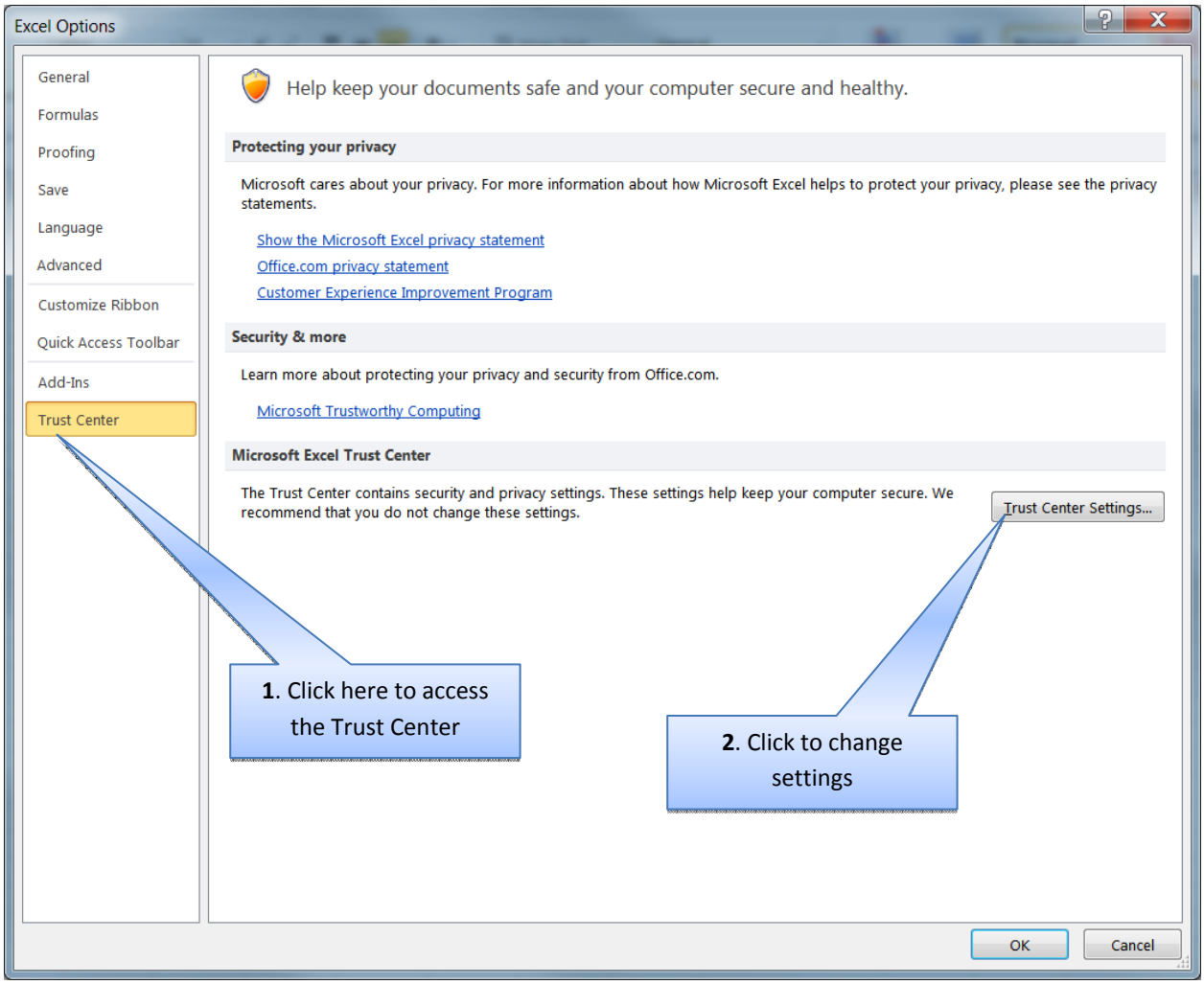


Figure 3 Accessing Excel Trust Center

After clicking on the Trust Center Settings, the Trust Center is displayed. Select the Macro Setting tab and check the Macro Setting "Disable all macros with notification" option (Figure 4). Click OK and close the tab and finally exit Excel. After making sure the macro settings are correct, TRIMMS can be started by double clicking on the application icon.

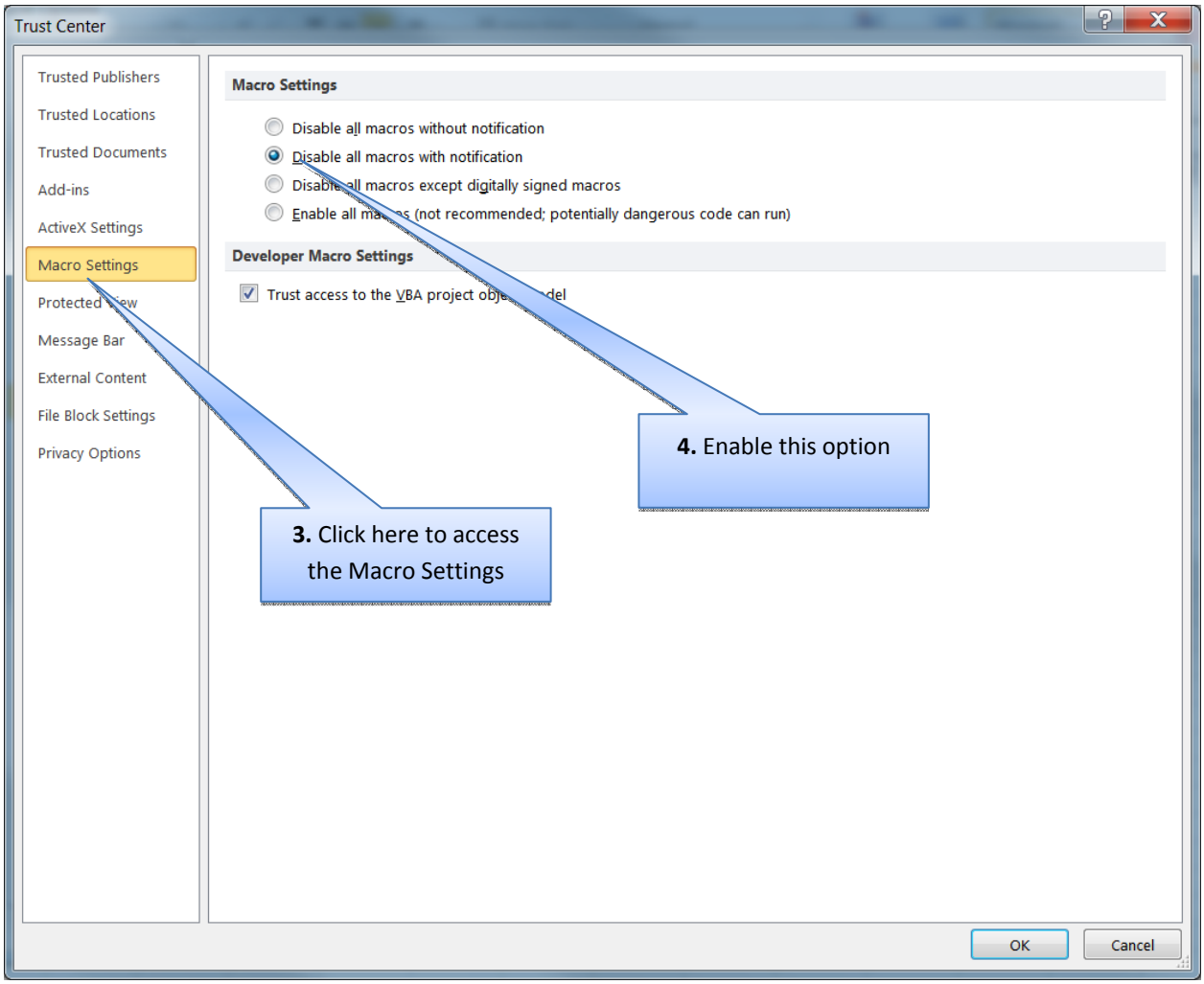


Figure 4 Customizing Macro Settings

When TRIMMS starts, Excel will provide a warning message about macro security. Enable the macro to run the application (Figure6).

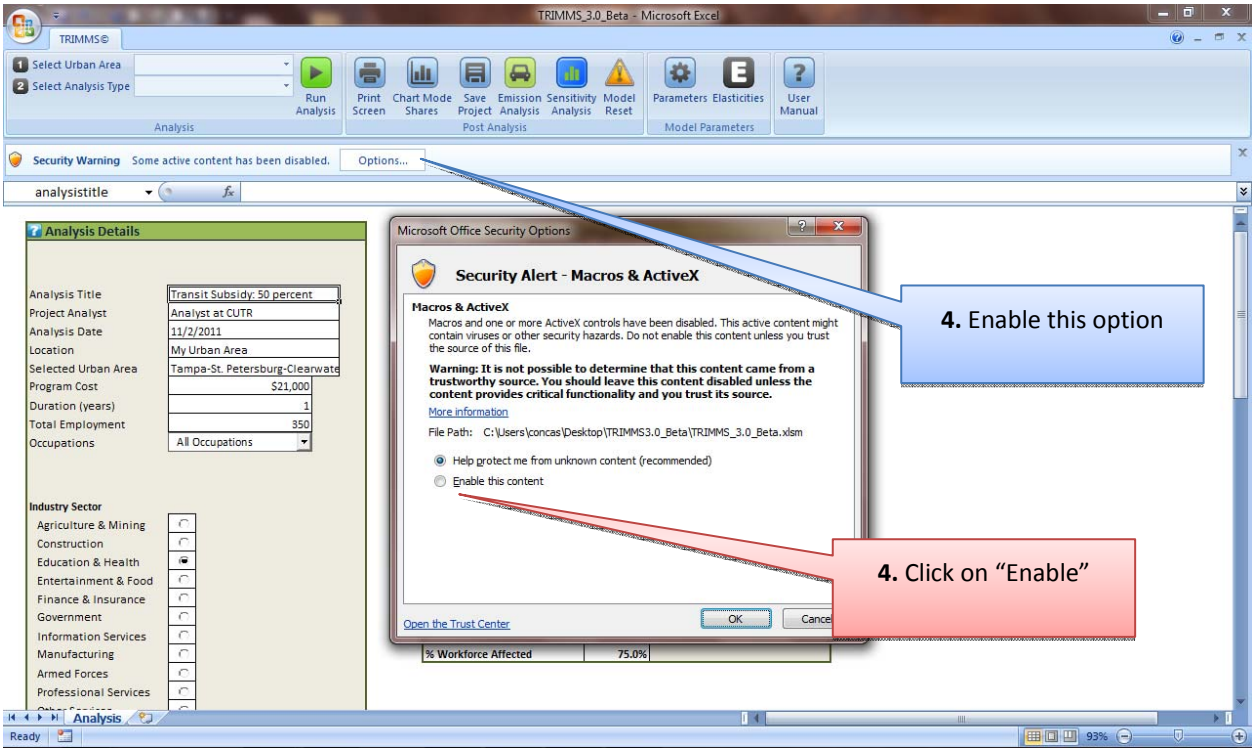


Figure 5 Macro Warning: Excel 2007

2.2 Navigating the Toolbar

Upon launching TRIMMS, a customized toolbar appears on the farther right of the Excel ribbon toolbar (Figure 6). All relevant actions can be performed by clicking on the appropriate buttons of this toolbar. There are three main groups of buttons:

1. Analysis
2. Post Analysis
3. Model Parameters

The analysis group contains three buttons required to run the analysis. To load the default parameters and analysis options, first select the urban area (Step1) and then select the Analysis Type option (Step 2). This step enables/disables options as they apply to a site-specific or regional (area-wide) type of analysis. After entering all required information into the Analysis worksheet, click on the "Run Analysis" button to run the model. The post analysis group contains a set of buttons to perform actions, such as printing the current screen, charting mode shares, saving the project, conducting sensitivity analysis, and resetting the model to its default values. The model parameters group contains a set of buttons to display inputs and underlying trip demand elasticities. The user manual can be called by pressing the appropriate button. Each of these functions is described in detail in this manual.

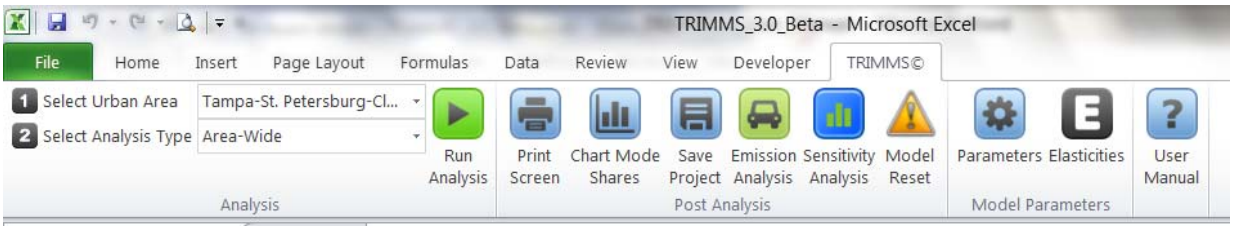


Figure 6 TRIMMS Toolbar

3. Analysis Worksheet

After selecting the urban area and the scope of analysis, the user can enter details about the projects. These are displayed in the "Analysis" worksheet, which is automatically loaded upon launching TRIMMS (Figure 7). This is the worksheet where all the project details are stored and evaluation of all strategies can be conducted. This worksheet is divided into four main sections:

1. Analysis Details
2. Employer-Based Commuter Programs
3. Strategies Affecting Travel Costs and Travel Times
4. Land Use Controls

If help is needed, the user can click on the help icon located on top left side of each section.

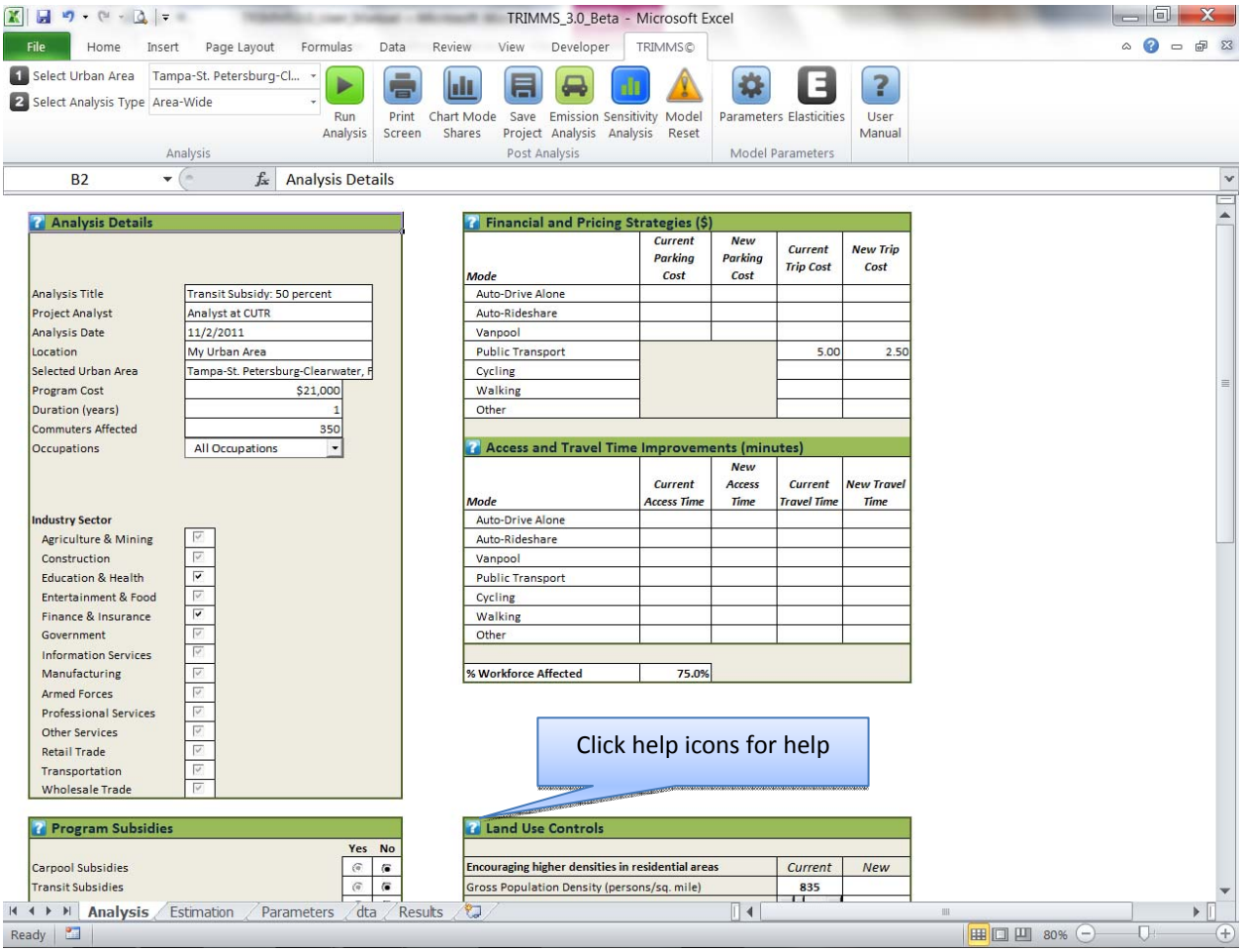


Figure 7 Analysis Worksheet

3.1 Analysis Details

In this section, users can enter details about a project (Figure 8). Note that to get results, the user must enter information on program cost, duration and approximate number of employees or commuters affected by the program.

The total number of employees defines the size of the commuting population under study and is used to compute baseline vehicle trips and vehicle miles of travel (VMT). Depending on the scope of analysis, this figure can represent the size of a single employment site, the total regional employment population, or a specific target population. For example, if running an area wide analysis, employers below a certain size might not be required to participate in any voluntary trip reduction program. Therefore, the user may want to restrict the analysis to employers of a relevant size and occupational industry.

Employer support programs tend to differ in terms of magnitude based on industry sector and size. If conducting a site-based analysis, the user can only select one industry sector. This choice is mutually exclusive (i.e., no more than one sector can be selected at the same time). This tailors specific inputs, such as the prevailing wage rate used to compute congestion cost changes and the calculation of employer support programs impacts.

If running an area wide analysis, the user can check the industry sectors that are likely to be affected by the program. One or more sectors can be checked, and if the policy affects all sectors, then the user can select all of them (Figure 9). This action calls the geographic area default industry composition information from TRIMMS database file and affects the calculation of baseline mode share changes, as well as impacting the estimation of travel time savings. Default data on sector employment levels and wage rates are displayed in the input worksheet as detailed in Section 5.2.4 of this manual. Wages are used to compute the congestion benefits a project might produce. These change according occupation and industry sector. To customize the wages to the analysis, the user must select the occupation type by clicking on the occupation list. This option also affects the program support evaluation as discussed in the next section.

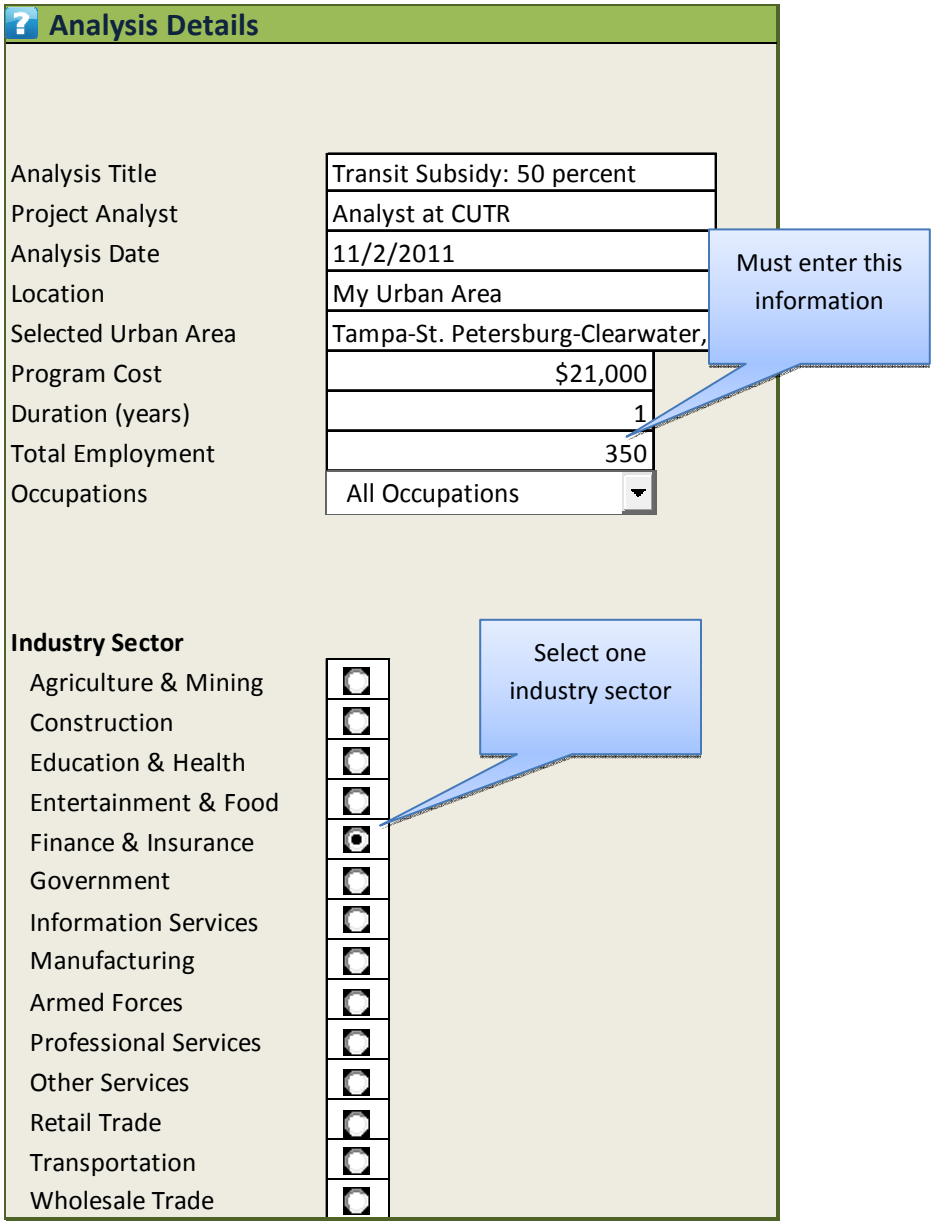


Figure 8 Site-Specific Analysis Industry Sector Options

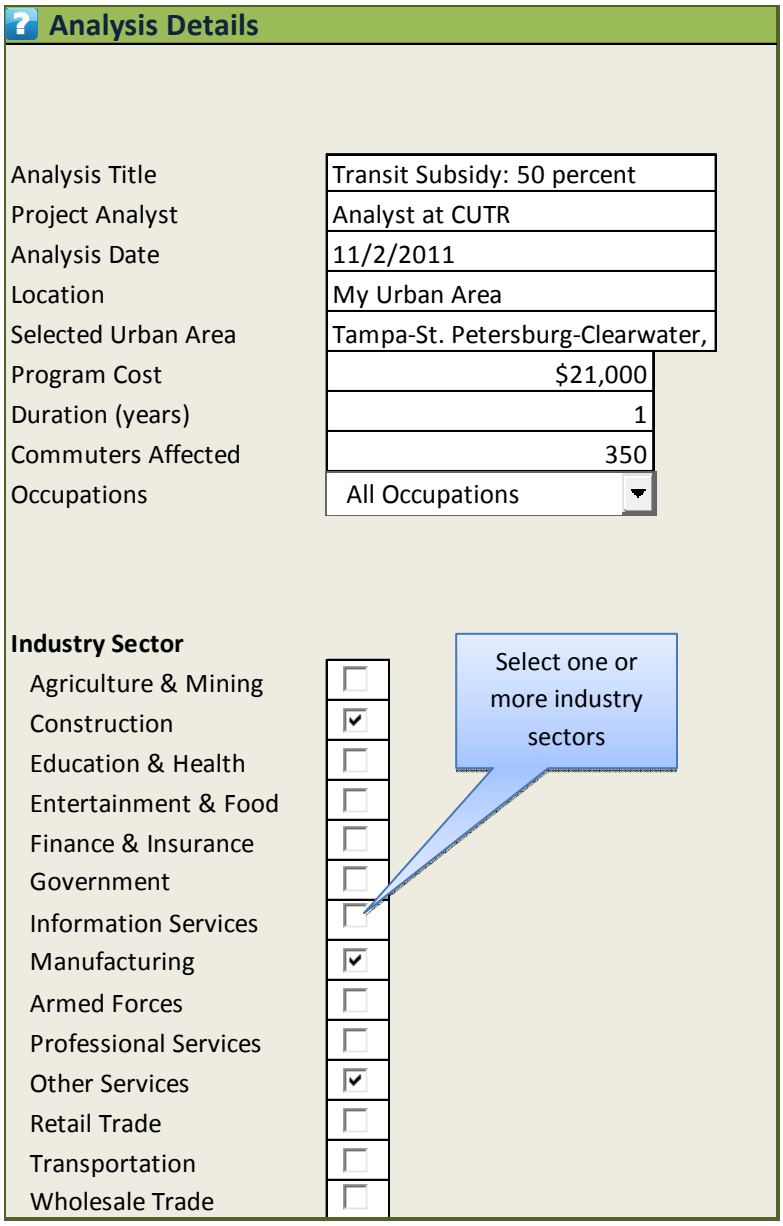


Figure 9 Area-Wide Analysis Industry Sector Options

3.2 Employer-Based Commuter Programs

In this section of the Analysis worksheet, users can select several options related to employer support programs. As part of a project evaluation, the user can estimate the impacts of one or a combination of several commute program strategies (Figure 10). For example, the user can simultaneously evaluate the impact of a telework initiative and the promotional effort that goes along with it. Selecting a given option calls specific parameters from a regression equation that predicts the mode share impacts. This action is similar the Environmental Protection Agency (EPA) COMMUTER model mode share balancing based on relational factors. The main difference is that TRIMMS does not use relational factors based on less subjective rules of thumb about the efficacy and intensity of TDM support programs. Rather it uses coefficients estimated from a fixed effect equation that the authors run on a commute trip reduction program of Washington State running over the course of three years. Details about the statistical technique and the estimation equation are provided in Appendix A2.

All options are disabled the first time TRIMMS is started and are reset if the scope of analysis changes. If area-wide is selected as the scope of analysis, then the options related to worksite characteristics are not enabled. This is because the effect of program marketing strategies is based on employer-specific actions that have an impact only at the worksite level.

Program Subsidies

	Yes	No
Carpool Subsidies	○	●
Transit Subsidies	○	●
Vanpool Subsidies	○	●
Bike Subsidies	○	●
Walk Subsidies	○	●

Guaranteed Ride Home and Ride Match

	Yes	No
Carpool matching service offered?	○	●
Emergency ride home provided?	○	●
Vehicle for non-work trips?	○	●

Telework and Flexible Work Schedules

	Yes	No
Flexible working hours offered?	○	●
Compressed work week offered?	○	●
Telework program offered?	○	●

Worksite Characteristics

	Yes	No
Accessibility		
Bus or train station onsite or within 1/4 mile	○	●
Bike lanes onsite or within 1/4 mile	○	●
Dedicated sidewalk onsite	○	●
Amenities		
Shopping onsite or within 1/4 mile	○	●
Restaurant onsite or within 1/4 mile	○	●
Bank onsite or within 1/4 mile	○	●
Childcare onsite or within 1/4 mile	○	●
Parking		
Parking charge for carpooling?	○	●
Parking charge for vanpooling?	○	●
Number of free onsite parking spaces	150	

Program Marketing

	Yes	No
Internal snail-mail of promotional material?	○	●
Internal promotional email?	○	●
Do you hold promotional events	○	●
Program management and promotion (hrs./week)	8	

Figure 10 Employer-Based Commuter Programs Evaluation

If running an area-wide analysis, then the selection of occupation type will affect the results. This is because TRIMMS assumes that not all occupations will be equally affected by employer support programs such as flexible working hours, telework or compressed work week. TRIMMS default occupation levels for a given MSA reflect total occupation for each industry sector. If the "all occupations" option is selected, then TRIMMS will assume that employer support programs will affect all commuters. If the user selects "administrative support" or "management" occupations, then TRIMMS will estimate impacts only for those occupations for the industry sector(s) selected. The percent of management and administrative support occupation are reported in the "Parameter" worksheet, which is discussed in Section 5 of this manual.

3.3 Strategies Affecting Travel Costs and Travel Times

In this section, users can assess different TDM strategies affecting the cost of travel (Figure 11). These include the evaluation of TDM incentives directly affecting the cost of using alternative modes either by directly lowering the cost of using a mode or indirectly in the form of a subsidy. This step also allows evaluating programs or policies geared at penalizing the cost of single-occupancy vehicle (SOV) use, such as parking price changes, pay-as-you-go schemes, and other policies affecting the cost of driving. For example, to evaluate a 50 percent reduction on a transit fare for a round trip, the user must enter the current amount charged and the new amount paid after the subsidy. As part of this step, users need to specify the percent of workforce affected by this policy.

Users can also evaluate service improvements that target mode access and travel times. This is especially important in the evaluation of transit accessibility improvements. For example, a user can estimate public transportation access improvements that reduce the overall time it takes a worker to go to work. When evaluating an employer site, average commute times are available from employee surveys. The user can enter the survey observed commute time before the implementation of access improvements and then enters the new, expected, travel time after the improvement. TRIMMS estimates mode share changes based on these numbers so that a user can estimate the benefits associated with accessibility improvements.

Financial and Pricing Strategies ($)

Mode	*Current Parking Cost*	*New Parking Cost*	*Current Trip Cost*	*New Trip Cost*
Auto-Drive Alone				
Auto-Rideshare				
Vanpool				
Public Transport			5.00	2.50
Cycling				
Walking				
Other				

Enter current and new fare/trip costs

Access and Travel Time Improvements (minutes)

Mode	*Current Access Time*	*New Access Time*	*Current Travel Time*	*New Travel Time*
Auto-Drive Alone				
Auto-Rideshare				
Vanpool				
Public Transport			15.00	10.00
Cycling				
Walking				
Other				
% Workforce Affected	**75.0%**			

Enter current and new trip travel times.

Specify percent affected

Figure 11 Strategies Affecting Travel Costs and Travel Times

3.4 Land Use Controls

This section is only enabled for area-wide program evaluation (Figure 12). This is because TRIMMS assumes that land-use programs or policies do not affect a specific employer worksite, but a broader area where commuters reside or work. Users can evaluate the impact of different land-use policies on the demand for transit services. Upon selecting a specific urban are, default gross population and retail establishment density levels are loaded, as well as the average distance. Parameters can be adjusted by moving the slide bars to simulate increases in density and accessibility levels. Note that accessibility is measured in distance to the nearest transit station. There is also a button that allows evaluation the impact of implementing a transit-oriented development (TOD)

transit station.[1] Users can also specify the percent of workforce affected by these strategies. Estimation of the impacts on transit patronage from land use controls is based on a set of land-use elasticity parameters produced by a simultaneous equation model of transit travel demand and urban form developed by Concas and DeSalvo (reference), and summarized in a working paper in Appendix A3.

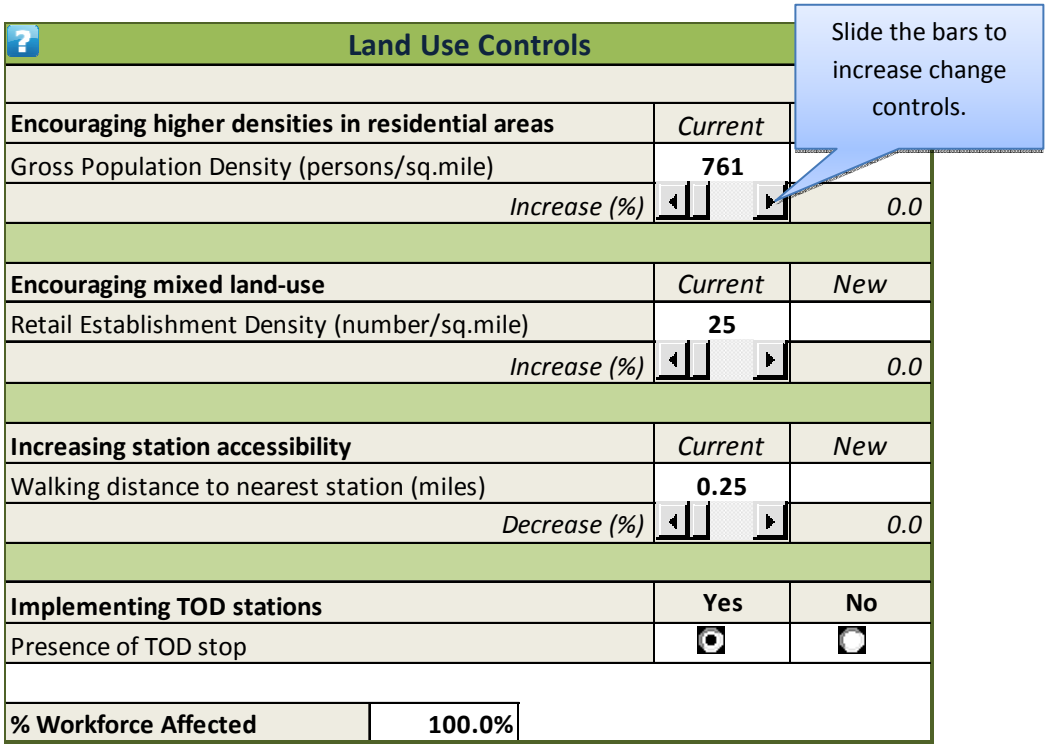


Figure 12 Land Use Controls Evaluation

4. Results Worksheet

After entering the project information, the user can run the model by clicking on the "Run Analysis" button located on the toolbar (Figure 13). TRIMMS performs all calculations and reports changes in mode share, trips, vehicle miles of travel, and changes in all relevant cost externalities. A summary of results is displayed in the "Results" worksheet (Figure 14).

Note that if the input and elasticity parameters are not customized before running the analysis, the TRIMMS' default values will be used. Users are encouraged to do a first run to see what TRIMMS estimates by default and then run a second analysis with customized inputs. This is discussed in more detail in the parameters section of this manual.

[1] A TOD station is characterized by land development policies geared at facilitating transit use by improving transit station accessibility (by reducing physical barriers), and by promoting mixed land-use development (residential and commercial) in their immediate surroundings.

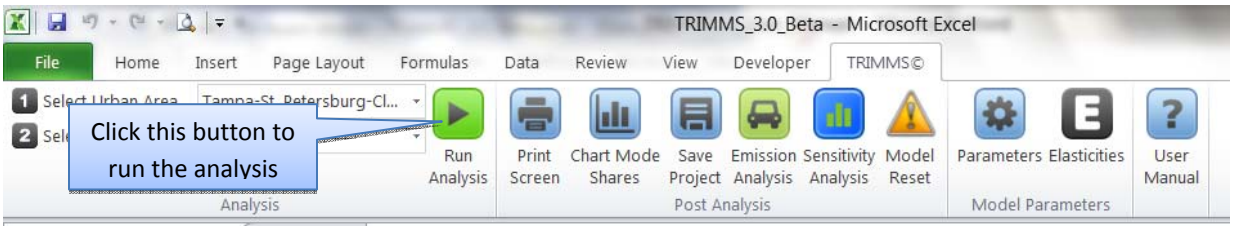


Figure 13 Running the Analysis

Users can print results, chart the changes in mode shares or save the project by clicking on the appropriate toolbar buttons. One main advantage of this upgrade is the capability of going back to the "Analysis" worksheet, change the underlying input parameters and re-run the analysis without the need to re-enter project details. For example, users can go back to the "Analysis" worksheet and change the options previously selected and re-run the model. Users are encouraged to print the screen before performing this action so that the results can be compared. Users can do this by clicking on the "Print Screen" button located on the tool bar (Figure 14).

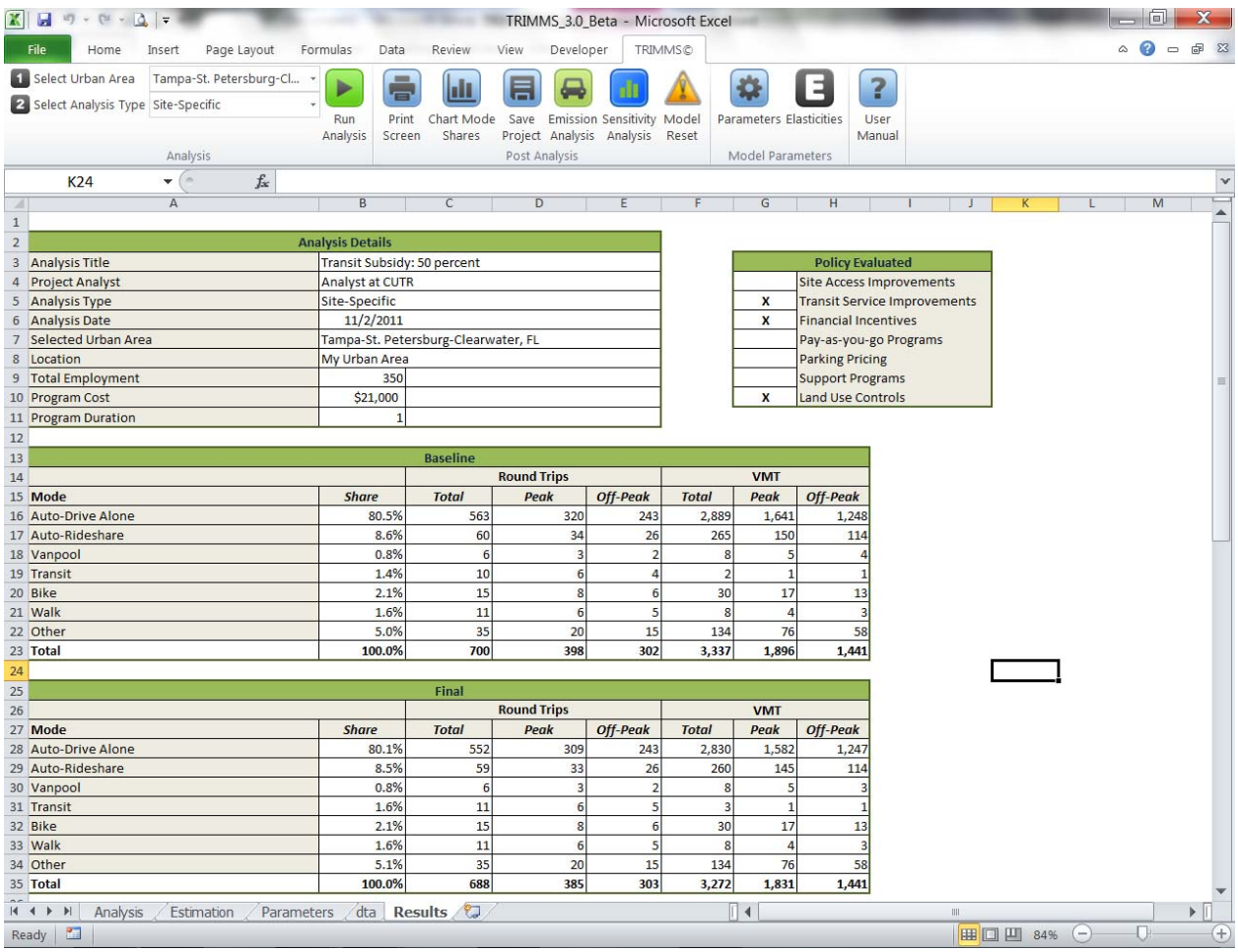


Figure 14 Worksheet Results

4.1 Baseline and Final Travel Behavior

The analysis worksheet reports all relevant results. It first displays the baseline mode shares, the number of round trips, miles of travel. Below the baseline values, it reports the estimated new mode values and then the difference between final and baseline values to gauge the impact on travel behavior of the project (Figure 15).

Change							
		Round Trips			VMT		
Mode	***Share***	***Total***	***Peak***	***Off-Peak***	***Total***	***Peak***	***Off-Peak***
Auto-Drive Alone	-0.33%	-11	-8	-3	-58	-42	-16
Auto-Rideshare	0.01%	-1	-1	0	-4	-4	0
Vanpool	0.00%	0	0	0	0	0	0
Transit	0.17%	1	0	1	0	0	0
Bike	0.03%	0	0	0	0	0	0
Walk	0.03%	0	0	0	0	0	0
Other	0.08%	0	0	0	0	0	0
Total	**0.00%**	**-11**	**-9**	**-2**	**-62**	**-46**	**-16**

Figure 15 Change in Travel Behavior (Final Estimates vs. Baseline Data)

4.2 Changes in Social Costs

TRIMMS also reports changes in social costs generated by the project and impacts on SOV travel behavior (Figure 16). Changes with a negative value correspond to a reduction in social costs and, therefore, represent a benefit. These values are reported in terms of daily dollar amounts. When annualized, the sum of these benefits produces the program total annual benefits, which are also reported. Finally, the results sheet produces a benefit-to-cost ratio for program evaluation purposes. TRIMMS provides estimates of changes in external or social costs associated with:

- Air pollution
- Added congestion
- Excess fuel consumption
- Global climate change
- Health and safety
- Noise pollution

These costs are defined as external costs, or costs associated with the choice of a particular mode and that are imposed to the society. For example, pollution costs, although not directly borne by a commuter using SOV to go to work, they are imposed on all other individuals. These costs are used in social benefit cost analysis to compare the costs and benefits associated with a given transportation alternative. Social and external costs are also relevant to pricing and are used to compare alternative plans for efficient use of transportation systems.

Impact on Auto-Drive Alone Travel			
(a negative value is a reduction)	**Peak**	**Off-Peak**	**Total**
Change in Daily Round Trips	-8	-3	-11
Change in Daily VMT	-42	-16	-58
Change in Gasoline Consumption (gallons/day)	-2.3	-0.9	-3.2

Change in Social Costs ($, Daily)			
(negative value is a reduction)	**Peak**	**Off Peak**	**Total**
Air Pollution	-0.03	-0.01	-0.03
Congestion	-64.1	-22.2	-86.32
Excess Fuel Consumption	-10.1	-3.4	-13.58
Global Climate Change	-0.37	-0.12	-0.49
Health and Safety	-0.76	-0.26	-1.03
Noise Pollution	-0.51	-0.19	-0.70
Total	***-75.90***	***-26.25***	***-102.15***

Figure 16 Impact on SOV Travel and in Social Costs

4.2.1 Changes in Air Pollution Emissions Costs

Air pollution costs are costs associated with emissions produced by motor vehicle use. Motor vehicles produce various harmful emissions that have negative effect at local and global levels. Exhaust air emissions cause damage to human health, visibility, materials, agriculture and forests [5, 6]. The major source of pollutants include carbon monoxide (CO), volatile organic compounds (VOCs), nitrogen oxide (NO_x), sulphur oxide (SO_x), and particulate matter (PM). Mobile emissions also affect global climate as gases increase the global warming effect. TRIMMS estimates changes in the costs associated with these pollutants. It also estimates changes in in emissions in absolute quantities (Kg/day) over the baseline case for a broader set of emission pollutants. These results are reported separately by clicking on the "Emission Analysis" button located in the toolbar.

4.2.2 Changes in Congestion Costs

TRIMMS estimates the costs associated with congestion delay produced by motor vehicle use. Congestion delay is the added delay imposed to all users as an additional vehicle is introduced into the traffic stream. Any TDM initiative that removes a vehicle from the road can potentially produce benefits in terms of changes or reductions in added delay. The cost of added delay is the opportunity cost of time spent on a motor vehicle for work or non-work related purposes; time that could be spent on other activities, such as leisure or other more work. This cost is a portion of the overall travel time costs since it only considers the portion of congestion costs generated by added delay to others.

4.2.3 Changes in Excess Fuel Consumption Costs

In addition to travel time-savings, added congestion contributes to excess fuel consumption. Research shows that TDM can contribute to reduce excess fuel consumption and thus reduce dependency from fossil fuel consumption [5, 7]. TRIMMS estimates the reduction of excess fuel consumption generated by a project in total gallons per day.

4.2.4 Changes in Global Climate Change Costs

Climate change costs quantify the damage associated with climate change. The Intergovernmental Panel on Climate Change (IPCC) defines climate change as the "state of any change in climate over time, whether due to natural variability or as a result of human activity [8]." Trapped heat in the atmosphere is a major driver of global climate change. Gases that trap heat in the atmosphere are called greenhouse gases. These include carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O) and fluorinated gases [9]. Motor vehicle fuel production and consumption release greenhouse gases, mainly CO_2, a major contributor to global climate change. EPA estimates that represents CO_2 about 30 percent of all greenhouse gas emissions [10]. There are mitigation and damage costs associated with global climate change. Damage costs are costs related to the environment, health, and reduced economic productivity.

TRIMMS estimates the impact that single occupancy vehicle use has on climate change. It measures changes in CO_2 emissions and measures the costs associated with each ton of this greenhouse gas.

4.2.5 Changes in Health and Safety Costs

Health and safety costs associated with crashes represent another relevant component of social costs. These include monetary costs, such as property and personal injury damages caused by collisions and cost avoidance activities, as well as nonmonetary costs, such as pain and loss of productivity. TRIMMS© estimates the change in comprehensive health and safety costs associated with changes in the number of vehicle crashes of the TDM initiatives under evaluation.

4.2.6 Changes in Noise Pollution Costs

Noise costs quantify the damage imposed on others from motor vehicle use. Motor vehicles produce noise from engine acceleration and vibration, from tire contact on road surfaces, from break and horn usage. Noise disrupts sleep, activities, causes stress, and negatively affects property values. Several studies analyze the impact and value of external costs associated with noise emissions. TRIMMS use default noise costs, measured in dollars per VMT, and estimates the total change in noise pollution costs resulting from a TDM initiative. As previously described, a negative value associated with any of these cost represent a reduction with respect to baseline values. A reduction is equivalent to a benefit generated by the TDM initiative under evaluation.

4.3 Program Cost Effectiveness

TRIMMS provide benchmarking measures in terms of annualized costs and annualized benefits, which produce a benefit-to-cost ratio.

4.3.1 Benefit to Cost Ratio Estimation

The sum of these daily reductions in social costs is a measure of the contribution of the TDM strategies evaluated under the project. Summed over the number of working days in a year, it gives the *Total Annual Benefits*. To obtain the Total Annualized Cost, the program total cost is annualized using the following formula:

$$Total\ Annualized\ Cost = P\left[\frac{i(1+i)^n}{(1+i)^n - 1}\right]$$

where P is the program total cost, i is the discount rate, and n is the length of the program, measured in years.
The ratio of Total Annual Benefits to the Total Annualized Cost produces the Benefit to Cost Ratio:

B/C Ratio= (Total Annual Program Benefits)/ (Total Annualized Program Cost)

This measure provides an economic assessment of how cost-efficient a TDM program is while producing positive benefits. The benefit-to-cost (B/C) ratio can be used as a cost effectiveness benchmark. A ratio equal to 1.0 indicates that for each dollar spent on the TDM program under evaluation there is a one-dollar return in terms of social benefits. Usually, the prioritization of transportation infrastructure investments for funding appropriation relies on the B/C ratio to produce a project-ranking list.

TRIMMS produces a summary of a project's net benefits and B/C ratios for peak, off-peak and a total B/C ratio (Figure 17).

Program Benefits			
(a positive value is a benefit)	**Peak**	**Off Peak**	**Total**
Total Annual Benefits (A)	$ 27,716	$ 9,598	$ 37,314
Total Annualized Cost (B)	$ 21,672	$ 21,672	$ 21,672
Net Benefit (A-B)	$ 6,044	$ (12,074)	$ 15,642
Benefit to Cost Ratio (A/B)	1.3	0.4	1.7

Figure 17 Net Program Benefits and Benefit-to-Cost Ratio

4.3.2 Sensitivity Analysis

Another feature of TRIMMS is the implementation of a Monte Carlo (MC) simulation module. Normally, all sketch-planning tools perform a series of calculations based on a set of inputs to provide estimates of parameters of interest. Results are provided in terms of single point estimates and there is generally no way to corroborate the robustness of these results. To compensate for this shortcoming, some models provide low and high point estimates [11]. A less subjective but technically challenging way to validate results is to conduct a sensitivity analysis using MC simulation methods. These methods are useful for modeling events with significant uncertainty in the values of inputs. This is especially true in the case of TDM evaluation, where there is a lot of uncertainty regarding the potential impact of TDM in terms of mode share changes and the resulting benefits. This is also relevant when modeling the changes in cost externalities, given that per unit-cost estimates vary dramatically across studies (like the cost of global warming).

In TRIMMS, the MC simulation module is set up to treat all social costs as random variables, while retaining the total annualized cost as deterministic (not subject to variation). Given the B/C formula, the resulting B/C ratio is itself a random variable. Through MC simulation, TRIMMS estimates its mean and the minimum and maximum values, defined as the 5th and 95th lower and upper boundary values of its distribution. These values give an idea of how likely the single point estimates provided in the "Results" worksheet are to occur if a project were to be implemented over and over again. Another question that the simulation can help answer is: "What is the probability that the B/C ratio will at least be greater than a certain value?" Often, transportation analysts are interested in knowing if the B/C cost ratio will at least be greater than 1.0 to guarantee some returns over each dollar invested in the program.

Suppose an analysis is run to obtain the B/C ratio of Figure 17. A user might want to test: 1) how likely are these numbers to vary due to input cost parameter variation, and 2) what is the probability that these values will be greater than 1.0 or any other threshold value.

To answer this question the user can run a simulation by clicking on the “Sensitivity Analysis” button located on the toolbar (Figure 18).

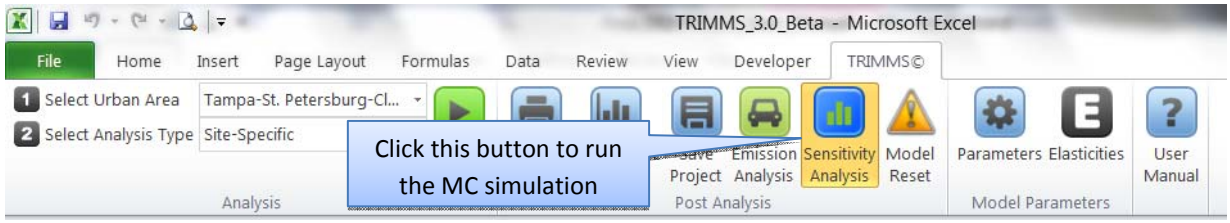
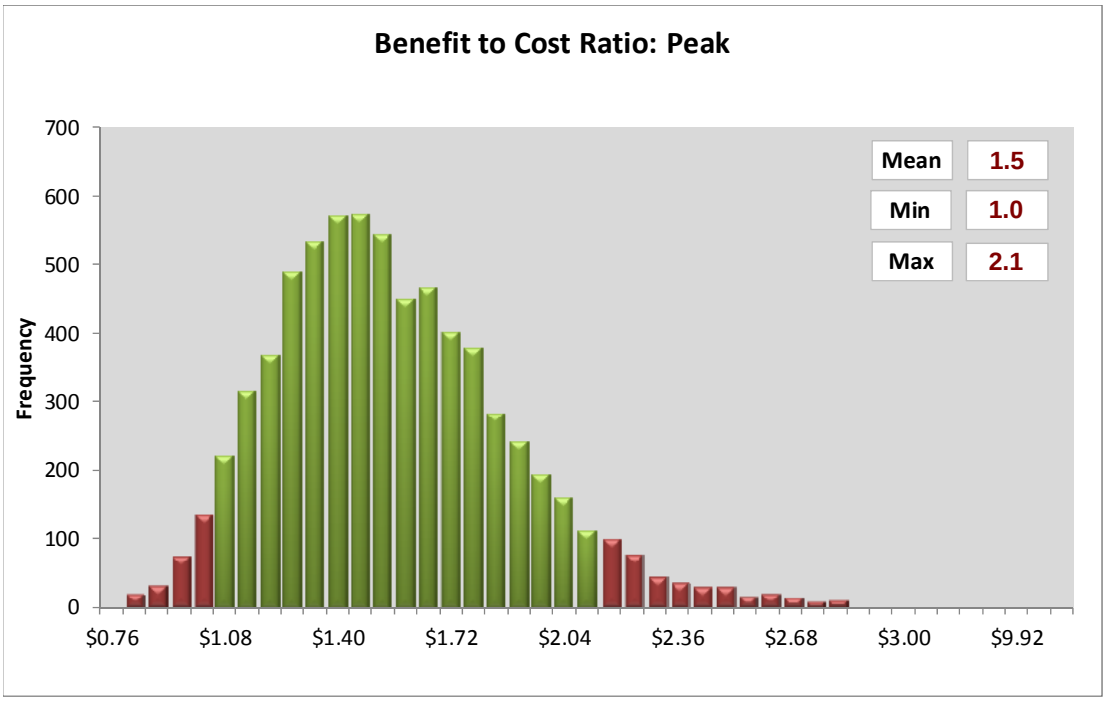


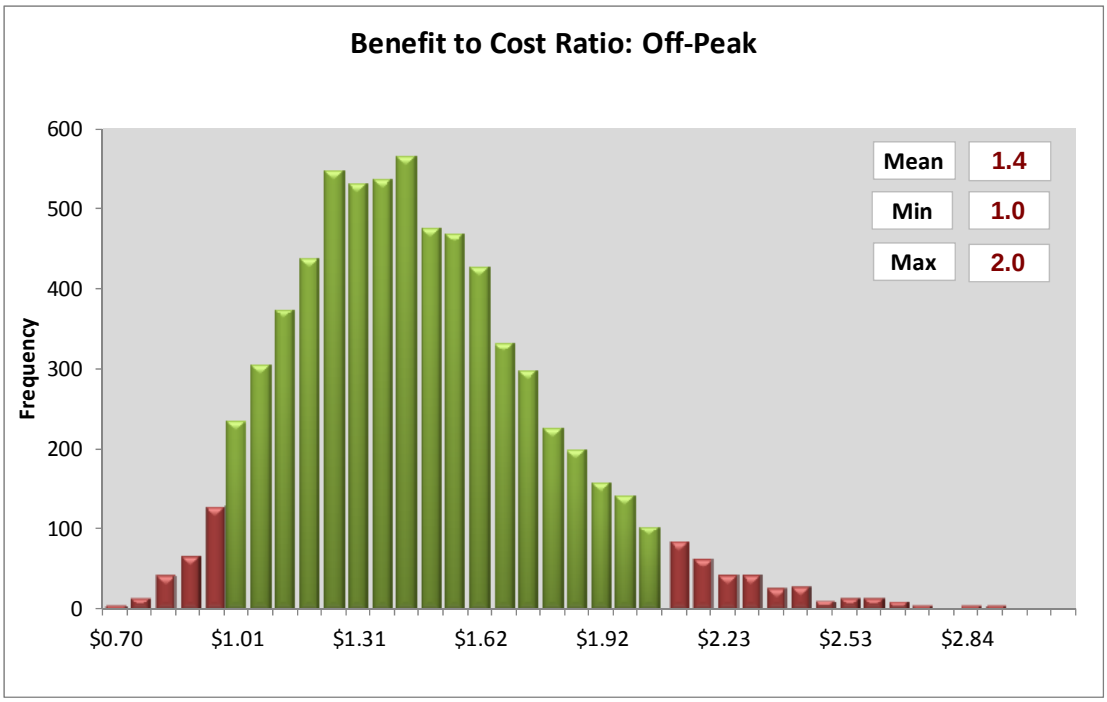
Figure 18 Sensitivity Analysis Button

By default, TRIMMS runs 7,000 iterations. On a typical personal computer (3.0 gigahertz processor and 2.0 gigabytes of random access memory) the simulation takes about one minute. Also, the default target B/C ratio is set at one dollar. To run the simulation faster and customize the target B/C ratio, click on the “Model Parameters” button and scroll down to the “Global Parameters” section. Note that selecting less than 3,000 iterations does not guarantee statistical robustness of the results. Upon clicking on the “Sensitivity Analysis” button, the MC simulation starts. A progress status bar located on the bottom left side of TRIMMS shows percent completion information.

Once the simulation is complete, TRIMMS displays two charts, along with the associated probabilities (Figure 18). The charts display the simulated B/C ratio distributions, the distribution mean and the minimum (5th percentile) and maximum (95th percentile) values. Under each chart is the estimated probability that the B/C ratio is greater than the target value.



Probability Benefit-to-Cost Ratio > 1	96.6%



Probability Benefit-to-Cost Ratio > 1	93.4%

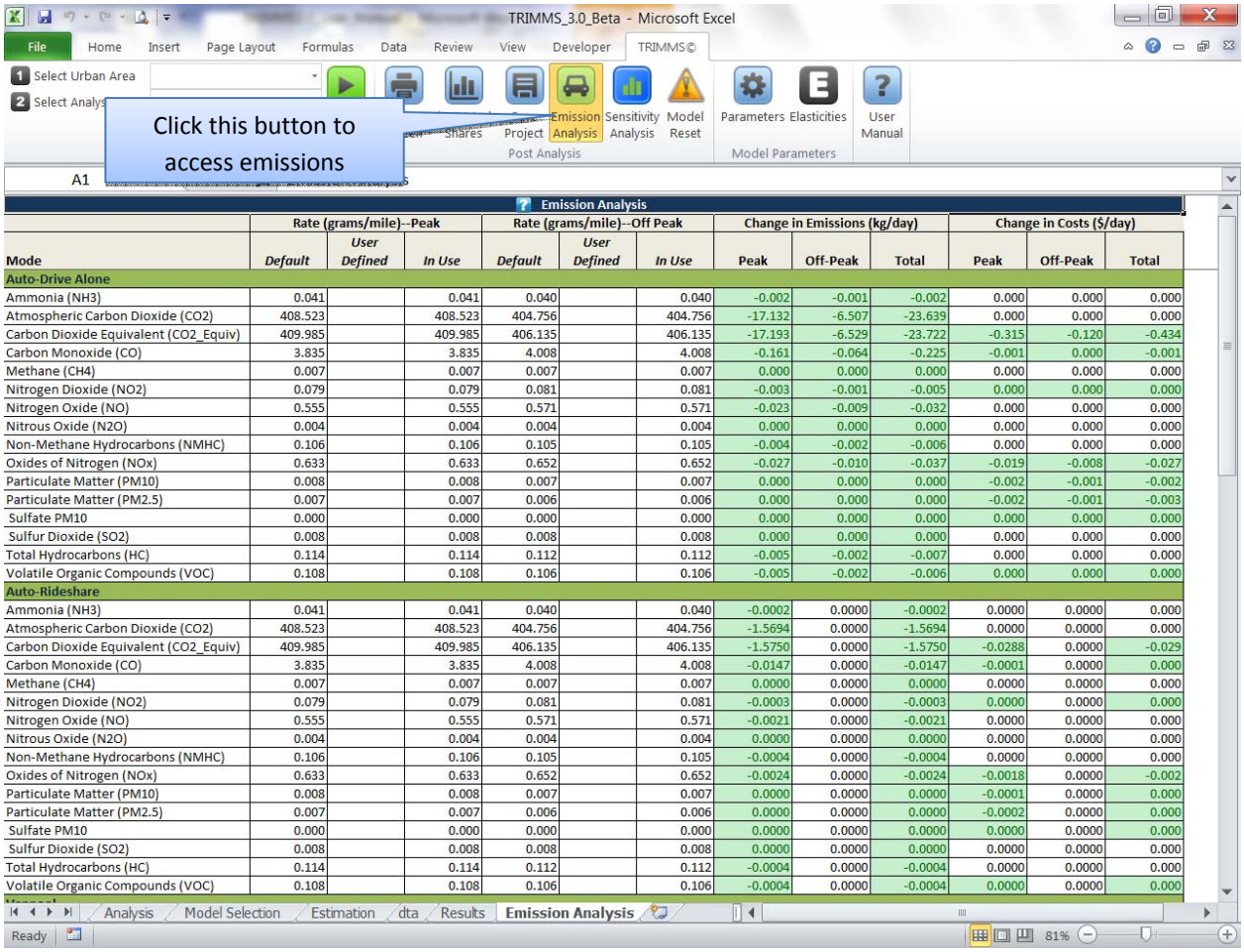
Figure 19 Sensitivity Analysis Results

4.4 Emission Analysis

TRIMMS now includes a separate worksheet that reports estimates of changes in emission pollutions. By clicking on the "Emission Analysis" button, the user can evaluate changes emission rates for the following air pollution emissions:

- Ammonia (NH3)
- Atmospheric Carbon Dioxide (CO2)
- Carbon Dioxide Equivalent (CO2_Equiv)
- Carbon Monoxide (CO)
- Methane (CH4)
- Nitrogen Dioxide (NO2)
- Nitrogen Oxide (NO)
- Nitrous Oxide (N2O)
- Non-Methane Hydrocarbons (NMHC)
- Oxides of Nitrogen (NOx)
- Particulate Matter (PM10)
- Particulate Matter (PM2.5)
- Sulfate PM10
- Sulfur Dioxide (SO2)
- Total Hydrocarbons (HC)
- Volatile Organic Compounds (VOC)

In this worksheet users can also customize the emission rates by entering custom values in the *User Defined* cells. Results showing an increase in daily emissions are highlighted in red, while reductions are highlighted in green (Figure 20). Once the data has been customized, click the "Emission Analysis" button again in the main toolbar to get back to the "Analysis" worksheet.



Emission Analysis

Mode	Rate (grams/mile)--Peak Default	User Defined	In Use	Rate (grams/mile)--Off Peak Default	User Defined	In Use	Change in Emissions (kg/day) Peak	Off-Peak	Total	Change in Costs ($/day) Peak	Off-Peak	Total
Auto-Drive Alone												
Ammonia (NH3)	0.041		0.041	0.040		0.040	-0.002	-0.001	-0.002	0.000	0.000	0.000
Atmospheric Carbon Dioxide (CO2)	408.523		408.523	404.756		404.756	-17.132	-6.507	-23.639	0.000	0.000	0.000
Carbon Dioxide Equivalent (CO2_Equiv)	409.985		409.985	406.135		406.135	-17.193	-6.529	-23.722	-0.315	-0.120	-0.434
Carbon Monoxide (CO)	3.835		3.835	4.008		4.008	-0.161	-0.064	-0.225	-0.001	0.000	-0.001
Methane (CH4)	0.007		0.007	0.007		0.007	0.000	0.000	0.000	0.000	0.000	0.000
Nitrogen Dioxide (NO2)	0.079		0.079	0.081		0.081	-0.003	-0.001	-0.005	0.000	0.000	0.000
Nitrogen Oxide (NO)	0.555		0.555	0.571		0.571	-0.023	-0.009	-0.032	0.000	0.000	0.000
Nitrous Oxide (N2O)	0.004		0.004	0.004		0.004	0.000	0.000	0.000	0.000	0.000	0.000
Non-Methane Hydrocarbons (NMHC)	0.106		0.106	0.105		0.105	-0.004	-0.002	-0.006	0.000	0.000	0.000
Oxides of Nitrogen (NOx)	0.633		0.633	0.652		0.652	-0.027	-0.010	-0.037	-0.019	-0.008	-0.027
Particulate Matter (PM10)	0.008		0.008	0.007		0.007	0.000	0.000	0.000	-0.002	-0.001	-0.002
Particulate Matter (PM2.5)	0.007		0.007	0.006		0.006	0.000	0.000	0.000	-0.002	-0.001	-0.003
Sulfate PM10	0.000		0.000	0.000		0.000	0.000	0.000	0.000	0.000	0.000	0.000
Sulfur Dioxide (SO2)	0.008		0.008	0.008		0.008	0.000	0.000	0.000	0.000	0.000	0.000
Total Hydrocarbons (HC)	0.114		0.114	0.112		0.112	-0.005	-0.002	-0.007	0.000	0.000	0.000
Volatile Organic Compounds (VOC)	0.108		0.108	0.106		0.106	-0.005	-0.002	-0.006	0.000	0.000	0.000
Auto-Rideshare												
Ammonia (NH3)	0.041		0.041	0.040		0.040	-0.0002	0.0000	-0.0002	0.0000	0.0000	0.000
Atmospheric Carbon Dioxide (CO2)	408.523		408.523	404.756		404.756	-1.5694	0.0000	-1.5694	0.0000	0.0000	0.000
Carbon Dioxide Equivalent (CO2_Equiv)	409.985		409.985	406.135		406.135	-1.5750	0.0000	-1.5750	-0.0288	0.0000	-0.029
Carbon Monoxide (CO)	3.835		3.835	4.008		4.008	-0.0147	0.0000	-0.0147	-0.0001	0.0000	0.000
Methane (CH4)	0.007		0.007	0.007		0.007	0.0000	0.0000	0.0000	0.0000	0.0000	0.000
Nitrogen Dioxide (NO2)	0.079		0.079	0.081		0.081	-0.0003	0.0000	-0.0003	0.0000	0.0000	0.000
Nitrogen Oxide (NO)	0.555		0.555	0.571		0.571	-0.0021	0.0000	-0.0021	0.0000	0.0000	0.000
Nitrous Oxide (N2O)	0.004		0.004	0.004		0.004	0.0000	0.0000	0.0000	0.0000	0.0000	0.000
Non-Methane Hydrocarbons (NMHC)	0.106		0.106	0.105		0.105	-0.0004	0.0000	-0.0004	0.0000	0.0000	0.000
Oxides of Nitrogen (NOx)	0.633		0.633	0.652		0.652	-0.0024	0.0000	-0.0024	-0.0018	0.0000	-0.002
Particulate Matter (PM10)	0.008		0.008	0.007		0.007	0.0000	0.0000	0.0000	-0.0001	0.0000	0.000
Particulate Matter (PM2.5)	0.007		0.007	0.006		0.006	0.0000	0.0000	0.0000	-0.0002	0.0000	0.000
Sulfate PM10	0.000		0.000	0.000		0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.000
Sulfur Dioxide (SO2)	0.008		0.008	0.008		0.008	0.0000	0.0000	0.0000	0.0000	0.0000	0.000
Total Hydrocarbons (HC)	0.114		0.114	0.112		0.112	-0.0004	0.0000	-0.0004	0.0000	0.0000	0.000
Volatile Organic Compounds (VOC)	0.108		0.108	0.106		0.106	-0.0004	0.0000	-0.0004	0.0000	0.0000	0.000

Figure 20 Emission Analysis Worksheet

5. TRIMMS Default Data

As in the previous version, TRIMMS provides default values for major U.S. urban area. Version 3.0 now includes default parameters for 100 U.S. metropolitan statistical areas (MSAs). These MSAs are representative of small, medium, large and very large urban areas.

TRIMMS uses global and regional parameters. Global parameters are default values that do not change by MSA, while regional parameters are values that are specific to a given area. Users can access and modify global and regional default input parameters by clicking on the "Parameters" button located in the toolbar, which displays the "Parameters" worksheet (Figure 21). Pressing the button again hides the worksheet and takes the user back to the "Analysis" worksheet.

5.1 Global Parameters

The following parameters are defined as global input parameters:

- Number of working days.
- Household income and population density – U.S. average.

- Consumer Price Index.
- Discount rate.
- Marginal added delay.
- Fuel prices.
- Fuel efficiency.
- Sensitivity analysis parameters.
- Social costs.

5.1.1 Number of Working Days

By default, TRIMMS assumes there are 235 working days in year. This implies that there are 10 days of holidays, 10 days of vacation, and 5 days of sick leave. Total annual benefits are obtained by multiplying daily benefits to the number of working days.

5.1.2 U.S. Median Household Income and Population Density

TRIMMS uses the ratio of regional median household income to median U.S. household income to obtain a regional scalar that accounts for differences in the cost living of between the 99 MSAs and the U.S. The regional scalar is then applied to the original estimates of various input costs whose values represent national averages to customize them to the selected MSA. The median household income comes from the 2005-2009 American Community Survey (ACS) [12].

To adjust the exposure to emission pollutants, TRIMMS scales the emission parameters using the ratio of MSA population density to the U.S average. The average population density is obtained from the U.S. Census Bureau.

5.1.3 Consumer Price Index

The *Results* sheet provides estimates of costs and benefits in current dollars. Since many of the inputs are culled from many sources and analyses conducted in different years, they must be adjusted from their original values. TRIMMS uses the Consumer Price Index (CPI) to translate all input costs in current dollars. For example, the U.S. median household income is reported in 2009 inflation-adjusted dollars. If the analysis is conducted in 2011 then we must use the following adjustment factor:

$$Adjustment\ Factor = \frac{CPI_{2011}}{CPI_{2009}} = \frac{223.6}{214.5} = 1.04$$

Then

$$U.S.\,Median\ Household\ Income\ (\$, 2009) = 51{,}369 * 1.04 = 53{,}539$$

TRIMMS uses the not-seasonally adjusted CPI for all urban consumers from the Bureau of Labor Statistics [13]. To allow running the analysis for future years, we forecasts CPI values for the years 2011-2020 assuming a 2.5 percent annual growth rate.

5.1.4 Discount Rate

TRIMMS uses the discount rate to convert the total program cost into an annualized cost by discounting it into constant-dollar flows. The default discount rate is 0.4 percent, which is equal to the 5-year real discount rate

published by the Office of Management and Budget of the White House and used for cost-effectiveness analysis [14].

5.1.5 Marginal Added Delay

Marginal added delay results from the presence of one extra vehicle on the road and is measured in added hours of delay per thousands of passenger-car equivalent (pce) VMT. TRIMMS employs a default value of 61.26 hours of delay per 1,000 pce VMT, as reported by Sinha and Labi [15] who referred to the Highway Economic System Requirements technical documentation [16]. The marginal added delay is used to compute changes in added congestions to others. This is explained in detail in the social cost section of this manual.

5.1.6 Fuel Prices and Fuel Economy

TRIMMS use the annual average cost per gallon of fuel net of taxes provided by the Energy Information Administration [17]. The estimate does not include taxes since they are a transfer from consumers to government or producers and do not represent an economic social cost. Note that while TRIMMS uses national averages, fuel costs are also adjusted using the regional scalar (ratio of MSA to U.S. median income). Fuel economy data for passenger cars and public transit come from the Bureau of Transportation Statistics [18]. Fuel price and fuel economy values are used to estimate the cost of excess fuel consumption.

5.1.7 Sensitivity Analysis Parameters

These are parameters needed to run the MC simulation of the B/C ratio, as discussed in Section 4.3.2. The default target B/C ratio is set at 1.0. It evaluates the probability that a project will return one dollar in benefits for each dollar of spent. The number of iteration is set at 7,000 and should not be changed, unless the user's computer has very limited processing capabilities.

5.1.8 Social Costs

TRIMMS uses default values to estimate changes in external costs generated by a project. Unit costs were culled from the literature for each of the categories of externalities. TRIMMS uses the CPI adjustment factor to translate all unit costs into current dollars. Section 5 provides detail on estimation and sources for each of the cost externalities.

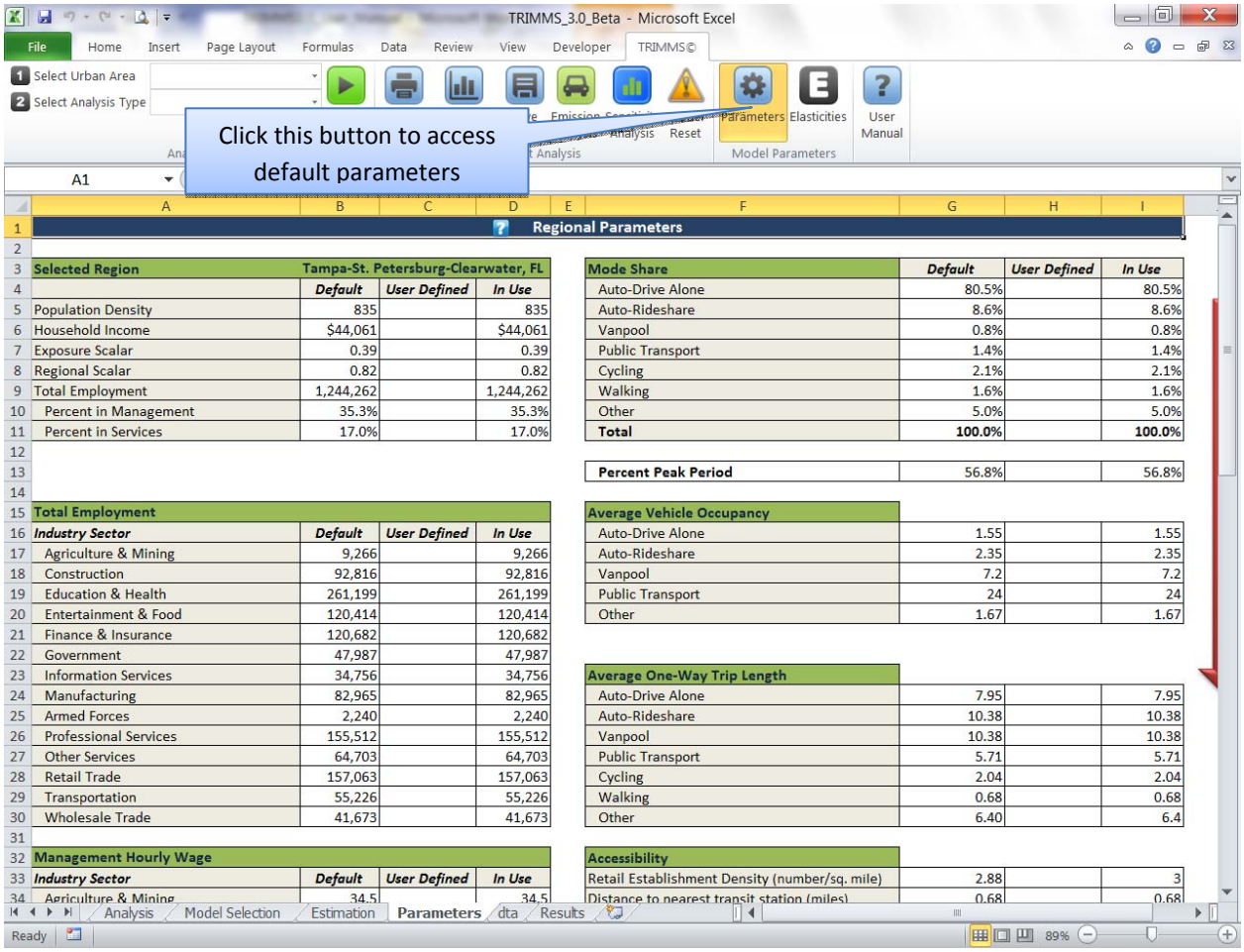


Figure 21 Parameters Worksheet

5.2 Regional Parameters

This is a set of parameters whose values are specific to the default MSAs or any other regional area the defined by the project's scope. The following parameters are defined as regional input parameters:

- Baseline travel behavior data
- Population and retail establishment density.
- Retail establishment density.
- Household income.
- Industry employment and wages.
- Accident rates

5.2.1 Baseline Travel Behavior Data

TRIMMS uses default mode shares, trip length, and vehicle occupancy levels to establish the baseline travel behavior data. Mode share estimates come from the 2007-2009 ACS (Table B08301), using mean values for workers 16 Years and over. Average trip length and vehicle occupancy come from the 2009 National Household Travel Survey. NHTS provides estimates for 50 of the MSA, and also by size of MSA. TRIMMS uses national averages for those MSA where average estimates are not available.

5.2.2 Population Density

Population density measures the number of persons per square mile. TRIMMS provides default population density estimates for all the 99 MSAs. As described in the next section, TRIMMS uses the ratio of population density to the U.S average population density to adapt the original pollution costs estimated by Delucchi [19] to the specific area under analysis. Population density estimates come from the U.S. Census Bureau Summary File 3 [20]. Population density is also used under the Land-Use Controls to estimate the change in transit travel resulting from policies affecting population density levels as part of an area-wide program evaluation. When customizing this input, users should use the U.S. Census Bureau Fact Finder and obtain population density estimates for the specific area of interest.

Retail establishment density measures the number of retail establishments per square mile. It is used as a proxy for land-use mix (commercial land uses) in the Land-Use Controls analysis. The number of retail establishments comes from the U.S. County Business Patterns [21].

5.2.3 Household Income

We use the ratio of regional median household income to median U.S. household income to obtain a regional scalar that accounts for differences in the cost living of between each MSA and the U.S. Median household income estimates come from the 2007-2009 ACS (Table B19013). When customizing this input to a region other than a default MSA, users should use U.S. Census Bureau Fact Finder.

5.2.4 Industry Employment and Wages

Industry employment and wages are used to estimate changes in congestion costs. Wages are employed to estimate the value of time for commuters and employment levels are used to weigh responsiveness to employer support program strategies. TRIMMS uses the May 2010 Bureau of Labor Statistic wage estimates by occupation type [22]. Employment levels by industry are obtained from the 2007-2009 ACS (Table B24050).

5.2.5 Accident Rates

TRIMMS provides baseline accident rates to estimate health and safety benefits. Accident data come from the National Highway Traffic Safety Administration Fatality Analysis Reporting System (FARS), which reports crash rates by severity. To substitute the default crash rates with area-specific values, the user can run a query on the FARS system [23].

5.3 Social Costs

To estimate changes in social costs, TRIMMS follows the methodology develop for the previous version by CUTR [2]. As described in the previous section, all of the default parameters associated with the social costs can be changed.

5.3.1 Congestion Costs

TRIMMS considers two congestion related external costs: the cost of added delay to others from vehicles entering into the traffic stream and the cost of excess fuel consumption due to lower average fuel economy in congested conditions.

The cost of added delay is the opportunity cost of time spent on a motor vehicle for work or non-work related purposes; time that could be spent on other activities, such as leisure or other more work. This cost is a portion of the overall travel time costs since it only considers the portion of congestion costs generated by added delay to others from vehicles entering into the traffic stream. The cost of added delay is the product of three values:

- Marginal added delay, measured in hours per thousand passenger-car equivalent (pce) VMT (hours/1,000 pce VMT).
- Daily vehicle miles of travel (VMT), estimated by TRIMMS.
- value of time, measured in dollars per hour.

The cost of congestion is equal to person-hours of delay multiplied by the cost per hour of time.

$$\text{Total cost of delay} = \text{Marginal added delay (hours/1,000 VMT)} \times \text{Change in daily pce VMT} \times \text{Value of time (\$/hour)} \times \text{Number of working days}$$

Following findings from a recently published NCTR report on the value of time [24], TRIMMS measure the value of time for commuting purposes as 100 percent of the prevailing average wage rate.

The total cost of excess fuel consumption is equal to the total annual gallons of excess fuel consumed, multiplied by the cost of fuel. We estimate changes in excess fuel consumption as:

Total cost of excess fuel consumption	=	Change in VMT	X	Average fuel economy (gallons/mile)	X	Fuel cost ($/gallon)	X	250 working days

For each area, we use the annual average cost per gallon of fuel net of taxes provided by the Energy Information Administration [17]. Taxes are a transfer from consumers to government or producers and do not represent an economic social cost.

5.3.2 Health and Safety

Another relevant component of social costs is represented by health and safety costs. These include monetary costs, such as property and personal injury damages caused by collisions and cost avoidance activities, as well as nonmonetary costs, such as pain and loss of productivity.

TRIMMS estimates the comprehensive health and safety costs associated with vehicle crashes as the total social cost per accident by severity type multiplied by the number of crashes in each severity class; its product summed over all severity classes.

$$Total\ Health\ and\ Safety\ Costs = \sum Total\ Crash\ Cost_i\ \ x\ Change\ in\ Number\ of\ Crashes_i$$

TRIMMS uses comprehensive cost estimates from the National Highway Traffic Safety Administration (NHTSA) report on the economic impact of motor vehicle crashes [25]. The report provides estimate of average economic and comprehensive costs by maximum abbreviated injury scale (MAIS). Economic costs consist of loss of human capital, market productivity, household productivity, medical care, property damage, and travel delay. NHTSA does not recommend using economic costs for cost-benefit ratios, since economic costs do not include the "willingness to pay" or intangible costs to avoid these events. The willingness to pay is included in the comprehensive cost estimates using a quality-adjustment life years (QALYs) factor loss. The comprehensive cost estimates are presented in Appendix A of the same report (Blincoe et al., 2002, Table A-1, pp. 62), which we report below in Table 3.2. TRIMMS automatically scales these costs for each region using the ratio of the region's median household income to the U.S. median household income.

Table 1 Monetary and Nonmonetary Accident Costs ($/occurrence, 2002 dollars)

	Property Damage Only	*No Injury*	*Minor Injury*	*Moderate Injury*	*Serious Injury*	*Severe Injury*	*Critical Injury*	
	PDO	*MAIS 0*	*MAIS 1*	*MAIS 2*	*MAIS 3*	*MAIS 4*	*MAIS 5*	*Fatal*
Medical	-	1	2,380	15,625	46,495	131,306	332,457	22,095
Emergency Services	31	22	97	212	368	830	852	833
Market Productivity	-	-	1,749	25,017	71,454	106,439	438,705	595,358
HH Productivity	47	33	572	7,322	21,075	28,009	149,308	191,541
Insurance Administration	116	80	741	6,909	18,893	32,335	68,197	37,120
Workplace Cost	51	34	252	1,953	4,266	4,698	8,191	8,702
Legal Costs	-	-	150	4,981	15,808	33,685	79,856	102,138
Subtotal	245	170	5,941	62,019	178,359	337,302	1,077,566	957,787
			Non-Injury Components					
Travel Delay	803	773	777	846	940	999	9,148	9,148
Property Damage	1,484	1,019	3,844	3,954	6,799	9,833	9,446	10,273
Subtotal	2,287	1,792	4,621	4,800	7,739	10,832	18,594	19,421
QALYs	-	-	15,017	157,958	314,204	731,580	2,402,997	3,366,388
Total	*2,532*	*1,962*	*10,562*	*66,819*	*186,098*	*348,134*	*1,096,160*	*977,208*

Source: NHTSA [25][2].

To obtain the change in number of crashes, we multiply changes in VMT estimated by TRIMMS by the crash rate of each severity.

Crash rates are positively related to traffic density, vehicle speeds, and roadway characteristics. For example, Kockelman [26] reports a nonlinear positive relationship between crash rates and vehicle speeds. Wand and Kockelman [27] find that crash rates vary according to vehicle type with light duty vehicles (minivans, pickups and sport utility vehicles) being associated with higher crash rates. Litman [28] provides empirical evidence that crashes increase with annual vehicle mileage and that mileage reduction reduces crashes and crash costs.

[2] The MAIS scale includes seven levels with: 0 = no injury; 1 = minor injury (whiplash, bruise); 2 = moderate injury (closed leg fracture, finger crush); 3 = serious injury (open leg fracture, amputated arm, major nerve laceration); 4 = severe injury (partial spinal cord severance, concussion); 5 = critical injury (complete spinal cord severance, concussion with loss of consciousness lasting more than 24 hours); Fatal (death).

We use the National Highway Traffic Safety Administration Fatality Analysis Reporting System (FARS) to obtain estimate of crash rates in number of crashes per million VMT. These estimates are based on historical information on crashes for all vehicle types by KABCO severity, *i*, and by road functional classification, *k*:

$$Crash\ Rate_{i,k} = \frac{Total\ Crashes_{i,k}}{Annual\ Million\ VMT_k}$$

where i = KABCO scale (K = killed; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = no injury); k = road functional classification (1 = arterial rural; 2 = arterial urban; 3 = freeway rural; 4 = freeway urban; 5 = collector rural; 6 = collector urban). To substitute the default crash rates with area-specific values, the user can run a query on the FARS system by clicking on the appropriate internet link below. VMT estimates come from the National Highway Administration Annual Highway Statistics series [29].

5.3.3 Air Pollution

Air pollution costs refer to costs associated with motor vehicle use. Motor vehicles produce various harmful emissions that have negative effects at local and global levels. Exhaust air emission cause damage to human health, visibility, materials, agriculture and forests [5, 6]. The major source of pollutants include carbon monoxide (CO), volatile organic compounds (VOCs), nitrogen oxide (NO_x), sulphur oxide (SO_x), and particulate matter (PM) of size 2.5 microns and less. Mobile emissions also affect global climate as gases increase the global warming effect. We discuss this issue in the next section. Pollution costs are the product of three values:

- emission estimates, measured in kilogram (kg)/mile.
- emission costs, measured in $/kg.
- vehicle miles of travel (VMT), estimated by TRIMMS.

For each mode *i* and each pollutant *k*, the total pollution cost PC is equal to:

$$PC_{ik} = \sum \left(\frac{kg_{ik}}{mile}\right)(VMT_i)\left(\frac{\$}{kg_k}\right)$$

These values are summed across all vehicle classes, pollutants, and impact categories to produce estimates of total pollution benefits of each TDM strategy being evaluated by the project.

To obtain accurate emission estimates we used the Environmental Protection Agency's (EPA) latest version of MOVES (Motor Vehicle Emission Simulator), which substituted the previous vehicle emission factor model MOBILE6.2 [3]. Estimates come from a batch-run of MOVES2010a for each metropolitan statistical area, using the national county-level emission inventory, and using estimates for weekday travel under peak and off-peak periods. Emission rates for each MSA represent a weighted average of emission at county level, accepting MOVES procedure to weigh the different vehicle stock, travel, and ambient conditions specific to each county. If using TRIMMS to obtain emission estimates to be used to conduct a transportation policy evaluation to meet transportation conformity regulations we strongly suggest customizing the TRIMMS emission factors following the policy guidance procedure recommended by EPA [30]. Alternatively users can contact the TRIMMS developer to inquire about a custom version of TRIMMS for a project. One of the major advantages of MOVES over MOBILE 6.2 is the wider range of air pollutants that can be modeled and the level of customization that can be achieved to

model a specific area. MOVES also provides estimates of global warming emissions (discussed next) in terms of CO2 equivalent estimates. TRIMMS comes loaded with emission rates for the following air pollution emissions:

- Ammonia (NH3)
- Atmospheric Carbon Dioxide (CO2)
- Carbon Dioxide Equivalent (CO2_Equiv)
- Carbon Monoxide (CO)
- Methane (CH4)
- Nitrogen Dioxide (NO2)
- Nitrogen Oxide (NO)
- Nitrous Oxide (N2O)
- Non-Methane Hydrocarbons (NMHC)
- Oxides of Nitrogen (NOx)
- Particulate Matter (PM10)
- Particulate Matter (PM2.5)
- Sulfate PM10
- Sulfur Dioxide (SO2)
- Total Hydrocarbons (HC)
- Volatile Organic Compounds (VOC)

Pollution emission costs are measured in $/Kg damages related to health and visibility impacts and physical impacts on the environment. We adopted the costs estimates of Delucchi [5], who estimated costs for several impact categories for urban areas of the U.S. in 1991. Delucchi recently updated the original values to account for changes in information about pollution and its effects [11]. He customizes these estimates by using regional exposure scalars to get from the average exposure basis in U.S. urban areas to the average exposure in each of the metropolitan statistical areas. According to Delucchi, population density is the best simple measure of exposure to air pollution. The original 1991 $/Kg are converted to current dollar values using the consumer price index (CPI). To account for cost of living geographical differences, these estimates are scaled to each individual region using the ratio of median household income of each area to the U.S. median household income.

5.3.4 Global Climate Change

The Intergovernmental Panel on Climate Change (IPCC) defines climate change as the "state of any change in climate over time, whether due to natural variability or as a result of human activity [8]." Trapped heat in the atmosphere is a major driver of global climate change. Gases that trap heat in the atmosphere are called greenhouse gases. These include carbon dioxide (CO_2), methane CH_4, nitrous oxide N_2O and fluorinated gases [9]. Motor vehicle fuel production and consumption release greenhouse gases, mainly CO_2, a major contributor to global climate change. EPA estimates that CO_2 represents about 30 percent of all greenhouse gas emissions. There are mitigation and damage costs associated with global climate change. Damage costs are costs related to the environment, health, and reduced economic productivity. We estimate the global climate change costs (GCCC) for each mode *i* as:

$$GCCC_i = \Delta VMT_i \; x \; CO_{2i}\left(\frac{kg}{mile}\right) \; x \; CO_2\left(\frac{\$}{kg}\right)$$

where ΔVMT_i is the change in VMT for mode *i* estimated by TRIMMS; $CO_{2i}\left(\frac{g}{mile}\right)$ represent CO_2 Equivalent emissions estimated by MOVES2010a; and $CO_2\left(\frac{\$}{kg}\right)$ is the marginal damage cost associated with CO_2 emissions.

TRIMMS estimate the marginal damage costs, or the cost of a change in greenhouse gas emissions associated with motor vehicle use. The unit of measure is the marginal damage in US dollars caused by a metric ton of CO_2 emissions ($/tC). Since cost estimates vary widely across the literature, we adopt the estimate of $50/tC by Tol [31] who analyzed and combined 103 estimates of marginal damage costs of carbon dioxide emissions from 28 published studies. We use the mean marginal damage cost that takes into account of only peer-reviewed literature (pp.2070). We scale this estimate down to dollar per kilogram ($/kg).

Note that while TRIMMS only considers the marginal damage costs associated with CO2 emissions, other authors provide more comprehensive estimates of greenhouse emission costs. For example, Delucchi [11] considers the global emission costs of pollutants other than CO_2 by calculating a ratio of CO_2 equivalent emissions to CO_2 emissions. Since EPA [9, 10, 32] considers these other greenhouse gases as more volatile and difficult to estimate, we follow EPA approach that only models CO_2 global emissions.

5.3.5 Noise Pollution

Noise costs refer to negative externalities associated with motor vehicle noise emissions. Motor vehicles produce noise from engine acceleration and vibration, from tire contact on road surfaces, from break and horn usage. Noise disrupts sleep, activities, causes stress, and negatively affects property values. TRIMMS estimates the total cost of noise emissions (NC) as:

$$NC_i = \Delta VMT_i \; x \; NC_{ik}\left(\frac{\$}{mile}\right)$$

where ΔVMT_i is the estimated change in VMT for mode *i*; NC_{ik}represents noise with *k* indicating rural or urban area.

Several studies monetize traffic noise costs (see for example, Delucchi [33]. We use noise cost estimates by Tod Litman [34], who comprehensively reviews the literature and provides estimates by mode type for urban and rural areas. These estimates are reproduced in the table below. In TRIMMS these costs are scaled to account for cost of living differentials between national averages and each regional area.

Table 2 Noise Pollution Costs

Mode	Urban Peak	Urban Off-Peak	Rural	Average
Average Car	0.013	0.013	0.007	0.011
Van/Light Truck	0.013	0.013	0.007	0.011
Rideshare Passenger	0.000	0.000	0.000	0.000
Diesel Bus	0.066	0.066	0.033	0.053
Motorcycle	0.132	0.132	0.066	0.106
Bicycle	0.000	0.000	0.000	0.000
Walk	0.000	0.000	0.000	0.000
Telecommute	0.000	0.000	0.000	0.000

Source:Litman [34]

5.4 Elasticity Parameters

As explained in more detail in Appendix A1, TRIMMS estimates changes in trips using trip demand functions that rely on constant elasticity of substitution (CES) parameters. Elasticities measure users' responsiveness to changes in pricing and travel times. Elasticities are used to measure the percentage change in demand of a good caused by a one-percent change in its price or other characteristics. For example, an elasticity of -0.5 for single occupancy vehicle trips with respect to fuel costs means that each 1 percent increase in the price of fuel results in a 0.5 percent reduction in the demand for vehicle trips.

TRIMMS trip demand functions make use of *direct elasticities* and *cross elasticities*. Direct elasticities refer to the percentage change in the demand for trips of any given mode resulting from a change in its own price or other measurable characteristics. Cross elasticities refer to the percentage change in the demand for trips of any given mode caused by a change in price or other measurable characteristics of other modes. For example, an increase in parking prices causes a direct negative percent change in the demand for auto trips and causes a positive change in the demand for transit services. The use of cross elasticities recognizes a certain degree of substitution, or mode shift, between transport modes; the intensity of substitution depending on circumstances and measured by the cross elasticities.

To obtain default parameters, we surveyed the empirical literature. There are a number of excellent surveys of the empirical literature on the demand for transportation and the role of elasticities [35-38]. TRIMMS uses parameters from these studies and other publications.

TRIMMS default elasticity parameters can be accessed by clicking on the elasticity button on the toolbar (Figure 22).

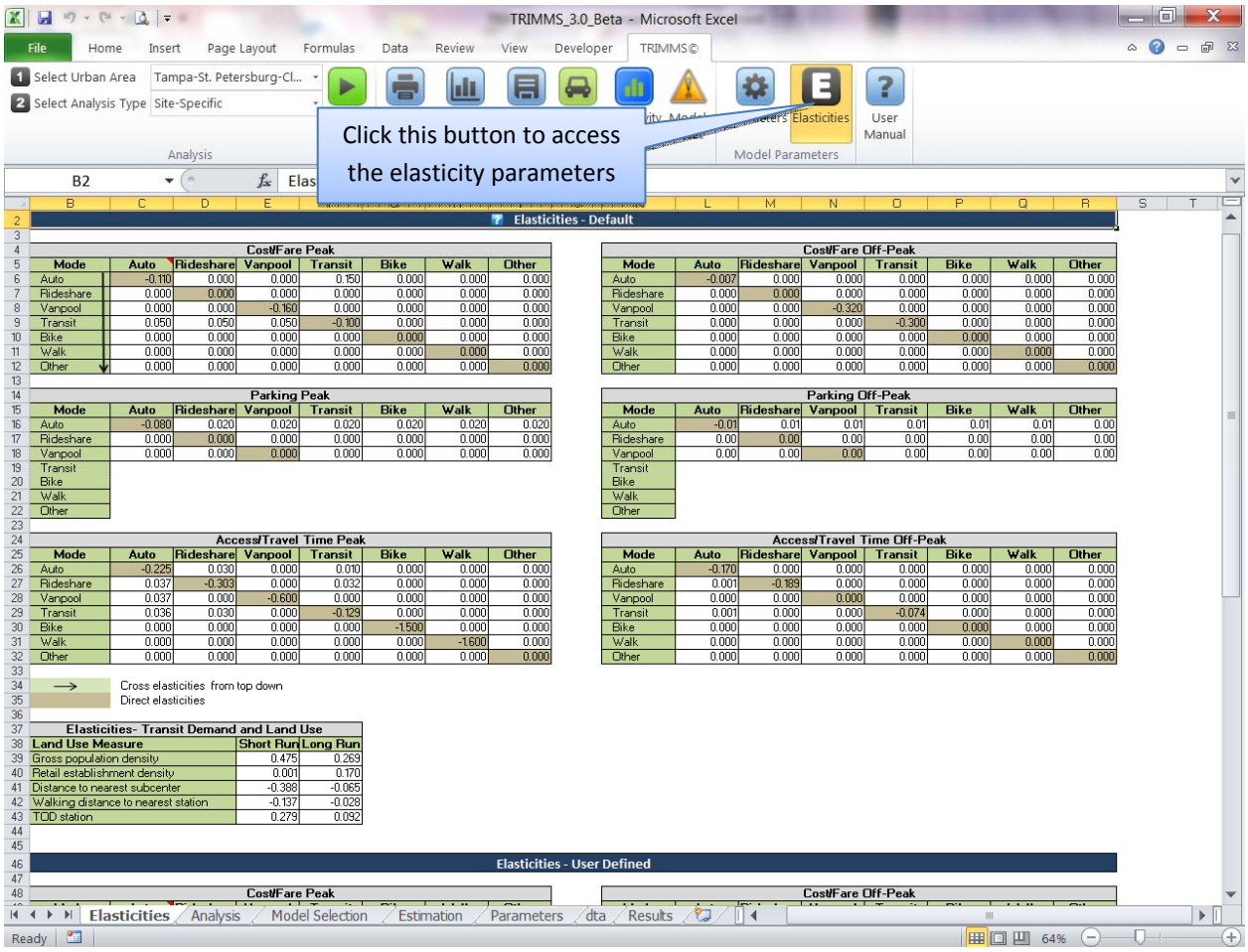


Figure 22 Accessing the Elasticity Parameters

5.4.1 Fare and Trip Cost Elasticities

Fare (and in general, pricing) elasticities are dynamic, as they vary over time. Researchers distinguish between short run and long run elasticity estimates. There are many definitions of short and long run, but most author define short run to be 1 or 2 years, and the long run to be about 12 to 15 years. Since most of the TDM programs run for a period corresponding to the short run, we adopted short run estimates as default values. These estimates are on average lower than the long run, signifying that users are less responsive to price changes in the immediate. Users can change all elasticity parameters by clicking on the *Elasticities* button located in the toolbar. Table 3 reports the default values estimates for direct and cross fare and price elasticities.

Table 3 Fare and Price Elasticities

Mode	*Elasticity*		*Source*	*Notes*
	short run	*long run*		
Auto - Drive Alone				
Direct	-0.047	-0.241	Hymel et al. [39]	Table 6, pp. 1232
Cross-Price: Transit	0.03	0.15	Litman (VTPI)	TRIMMS uses the lower ranges
Auto - Rideshare		-0.241		
Direct	-0.047		Hymel et al.[39]	Table 6, pp.1232
Cross-Price: Transit	0.03	0.15	Litman (VTPI)	same as auto-drive alone
Vanpool				
Direct	-0.73	-1.46	Concas et al.[40]	Long run twice of short run
Cross-Price: Auto - Rideshare	n/a	n/a	n/a	n/a
Transit				
Direct: Peak	-0.59	-0.75	Holmgren et al. [41]	Table 6
Direct: Off-Peak	-0.89	-1.13	Our assumption	Our assumption: assume 1.5 times of peak
Cross-Price: Auto - Drive Alone	0.05	0.20	Litman (VTPI)	We use the lower ranges

We adopt the transit fare elasticity estimates of Holmgren [41], who performs a meta-analysis of fare, income, level of service elasticities and vehicle ownership. These estimates are somewhat higher than the estimates of some other authors. For example, Litman [38]reports short run elasticities between -0.2 and -0.5 and between -0.6 and -0.9 for the long run.

Table 4 reports the direct and cross travel time elasticities based on estimates by Litman [38] who provides a comprehensive review of travel time elasticities.

Table 4 Travel Time Elasticities

Mode	*Elasticity*		*Notes*
	Peak	*Off Peak*	
Auto - Drive Alone			
Direct	-0.225	-0.170	
Cross: Auto - Rideshare	0.030	0.000	
Cross: Transit	0.010	0.000	
Auto - Rideshare			
Direct	-0.303	-0.189	
Cross: Auto - Drive Alone	0.037	0.000	
Cross: Transit	0.032	0.000	
Vanpool			
Direct	-0.303	-0.189	We assume same as Auto: Rideshare
Cross-Price: Auto - Rideshare/Drive Alone	0.037	0.000	
Cross: Transit	0.032	0.000	
Transit			
Direct	-0.129	-0.074	
Cross: Auto - Drive Alone	0.036	0.000	
Cross: Auto - Rideshare	0.030	0.000	

Source: Litman [37]Table 31, pp. 35

5.4.2 Parking Demand Elasticities

Parking elasticity estimates are derived from a meta- analysis of elasticities culled from the literature. Results from a linear regression of 162 elasticity estimates from 25 studies produced the table below [42]. Cross price and slow mode elasticity estimates come from Litman [38] (Table 5).

Table 5 Parking Pricing Elasticities

Parking Elasticities				
Trip Purpose	*Auto - Drive Alone*	*Auto - Rideshare*	*Transit*	*Slow Modes*
Commuting	-0.158†	0.02††	0.02††	0.02††

Source:
† Concas and Nayak (2011)
††Litman (2008), Table 13, pp. 17

5.4.3 Land Use Control Elasticities

TRIMMS employs CES elasticity parameters to translate change in urban form and land-use variables into changes in transit patronage levels. TRIMMS assumes that an increase in transit demand is equivalent to a decrease in auto-drive demand by the same magnitude. Under a separate project, CUTR developed and analytical framework that models transit demand, residential location patterns, trip-chaining behavior and transit patronage levels [43]. The comprehensive modeling framework produced a set of land-use elasticities that can be used at the sketch-planning level by practitioners in the field. Short-run elasticity consider density levels and residential location and work patterns as exogenous or predetermined, while long-run estimates treat all variables as endogenous (Table 6). Based on the project duration, TRIMMS selects the proper set of parameters. For a synopsis of the methodology to estimate the land-use elasticities, see the working paper of Appendix A3.

Table 6 Land-Use Elasticity (Concas and DeSalvo, 2008)

Elasticity	*Short Run*[a]	*Medium Run*[b]	*Long Run*[c]
Density	0.475	0.269	n/a
Walking distance to nearest station	-0.137	-0.028	-0.093
*Transit station at workplace**	0.687	0.766	0.961
*TOD station**	0.279	0.139	n/a
Retail establishments density	0.001	0.170	n/a

[a] residential location exogenous; density exogenous

[b] residential location endogenous; density exogenous

[c] residential location and density endogenous

n/a = not available

* Indicates a proportional change

Source: Concas and DeSalvo[43]

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Appendices

A1. Constant Elasticity of Substitution Trip Demand Functions

TRIMMS predicts mode share and VMT changes brought about by TDM initiatives affecting the cost of travel by using constant elasticity of substitution trip demand functions. These functions estimate changes from baseline trip demands taking into account users' responsiveness to changes in pricing and travel times.

The following example is designed to provide a better understanding of the relationship between price and travel time elasticities and how these relate to travel behavior. We assume that there are two modes, auto and transit; and, that the trip demand functions depend solely on fare costs and travel times. Let us assume the following travel demand function for auto:

$$d_i = AP_i^{\epsilon_i^P} T_i^{\epsilon_i^T} T_j^{\epsilon_{i,j}^T} \ldots \qquad \text{(A.1)}$$

Where:

d_i= demand for auto travel, measured in person trips per day

j= transit mode

A= scale parameter

P_i = car travel fuel price

T_i= car travel time

T_j= transit travel time

ϵ_i^P= car trip cost elasticity

ϵ_i^T= car travel time elasticity

$\epsilon_{i,j}^T$= car travel time cross-elasticity with respect to transit travel time

We specify the demand function using a constant-elasticity demand function because of its wide empirical application in the estimation of travel demand elasticities and for its ease of analytical tractability.[3]

[3] The demand curves usually employed and depicted in graphs are linear demand curves, which have the property that price elasticity declines as we move down the demand curve. Not all demand curves have this property, however; on the contrary, there are demand curves for which price elasticity can remain constant or even rise with movements down the demand curve. The *constant elasticity demand curve is* the name given to a demand curve for which elasticity does not vary with price and quantity. Whereas the linear demand curve has the general form $P = a - bQ$, the constant elasticity demand curve is instead written as:

$$P = \frac{k}{Q^{\frac{1}{\eta}}}$$

Where *k* and *η* are positive numbers that determined the shape of the curve.

The price elasticity of a car measures the percent reduction in trips due to a one percent increase in its price. The travel time elasticity of demand measures the percent reduction in trips due to a one percent increase in travel time. Finally, the car travel time cross elasticity with respect to transit travel time measures the percent reduction in trips due to a one percent decrease in transit travel time. We assume that car and transit are substitutes.[4]

Now, for initial values of fuel price, time and trips, denoted by subscript zeros, the auto trip demand is:

$$d_{i0} = AP_{i0}^{\epsilon_i^P} T_{i0}^{\epsilon_i^T} T_{j0}^{\epsilon_{i,j}^T} \ldots \tag{A.2}$$

Solving for *A* in (A.*2*) and substituting the results back into *(A.1)*, we can eliminate the scale parameter A and ensure that the demand function passes through the point (d_0,P_0,T_0). The resulting equation is:

$$d_i = d_{i0} \left(\frac{P_i}{P_i}\right)^{\epsilon_i^P} \left(\frac{T_i}{T_i}\right)^{\epsilon_i^T} \left(\frac{T_j}{T_j}\right)^{\epsilon_{i,j}^T} \tag{A.3}$$

Then, for a given change in trip costs and travel times, the new number of vehicle trips is obtained by substituting the new costs and travel times into equation *(A.3)*, giving:

$$d_i = d_{i0} \left(\frac{P_{i1}}{P_{i0}}\right)^{\epsilon_i^P} \left(\frac{T_{i1}}{T_{i0}}\right)^{\epsilon_i^T} \left(\frac{T_{j1}}{T_{j0}}\right)^{\epsilon_{i,j}^T} \tag{A.4}$$

Finally, what we are interested in is the change in the number of vehicle trips, which is given by:

$$\Delta d_i = d_{i0} \left[\left(\frac{P_{i1}}{P_{i0}}\right)^{\epsilon_i^P} \left(\frac{T_{i1}}{T_{i0}}\right)^{\epsilon_i^T} \left(\frac{T_{j1}}{T_{j0}}\right)^{\epsilon_{i,j}^T} - 1 \right] \tag{A.5}$$

This last formula constitutes the approach to model the change in demand brought about by program or policies affecting the perceived cost of travel, both monetary and non-monetary. Equation *(A.5)* can be simplified or expanded to include additional cost factors and to comprise cross relationships with one or more modes.

Advantages and Constraints

There are different ways of providing a simple, yet powerful and robust approach to estimating the impacts of alternative strategies at a sketch planning level. The constant elasticity of demand approach proposed requires basic information on the cost and time components of modal trips, and on the initial mode share. By entering the

[4] Two goods are considered substitutes if the increase in the price of one determines an increase in the demand for the other. Two goods are considered complements if the increase in the price of one good causes a decrease in the demand for both goods (e.g., coffee and cream). The relationship is further refined by considering perfect versus less-than-perfect substitution and complement.

impact on the generalized cost of travel of a given policy or program, the model estimates the impact on the final mode shares. These data requirements are described in greater detail in this report.

The model estimates impacts on travel behavior in a synergistic fashion. That is, the model allows the simultaneous impact assessment of several TDM policies or strategies, where the final total impacts are greater than the sum of the impact of each individual strategy. In addition, the constant elasticity of demand equation *(A.5)* assures that impacts are assessed in a multiplicative, rather than an additive, fashion avoiding impacts overestimation. For example, if one strategy (e.g., a transit subsidy) reduces SOV use by 5 percent and another strategy, say parking pricing, reduces SOV use by an additional 7 percent, the total combined effect is a 11.5 percent reduction(calculated as 100% - [95% x 93%]), rather than a 12 percent reduction (linearly calculated as 7% + 5%).

Another advantage of the model is that it allows program evaluation based on *incremental* impacts. For example, under the constant elasticity demand framework the congestion reduction benefits of a shift from SOV to transit is the difference in congestion impacts between SOV and transit travel. Using a base case approach (a scenario where a policy or program is not implemented), the model estimates the net benefits of shifting from SOV to alternative modes. Also, the model permits distinguishing between peak and off-peak impact estimation at an urban area level.

One of the constraints related to the use of elasticities relates to timeframes employed when empirically estimating their values. Applied work generally employs short and medium terms (3-5 years), thus tending to underestimate the full, long term effects of price and service changes. In other terms, increasing (reducing) a transit fare has more negative (positive) effects than what generally predicted by most models. The constant elasticity of demand model is best suited for strategies that directly affect the generalized cost of driving, and a set of TDM strategies, such as:

- Parking pricing.
- Modal subsidies.
- Pay-as-you-go schemes.
- Transit service improvements.
- Other interventions affecting the cost of driving or modal access and travel time.

These strategies often integrate both incentives and disincentives. The latter are usually defined as “sticks” and comprise actions geared at directly influencing the cost of driving, such as increased auto user charges, parking pricing, and traffic calming.

A2. Program Support Evaluation

Program support strategies that are designed to enhance voluntary behavior changes are usually defined as “carrots” and usually consist of measures geared either at increasing the knowledge of alternative modes and programs or at internalizing some of the costs associated to driving that would otherwise be borne by others. Examples of soft program initiatives include:

- Travel Planning.
- Advertising.
- Flexible Work Hours.
- Telecommuting.
- Guaranteed Ride Home Programs.
- Discount for Walking and/or Cycling Gear.

Although these programs do not directly affect the cost of using a mode, they tend to impact travel behavior when part of a program consists of hard measures. Generally, it is not possible to directly estimate change in travel behavior from these TDM strategies.

To evaluate the impact of program support strategies on travel behavior, TRIMMS© relies on an econometric analysis of the relationship between hard and soft programs of the Washington State Department of Transportation Trip Reduction Program. We first prepared a dataset covering the period 1995 to 2005. The data reports information on worksite characteristics, such as firm size and industry type, employee mode share, and information of TDM programs.

We specify a regression equation where each of employer support programs enters into an empirical equation estimating the change in ridership as an explanatory variable in a context of interaction with hard programs.[5] The regression equation takes the form:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \epsilon \qquad \text{(A.7)}$$

Where y is the dependent variable, in this case vehicle trip rate at worksite; $x_1, x_2, \ldots x_k$ are explanatory variables (soft and hard program policies, firm characteristics, other controls); and ϵ is a stochastic or error term. Equation *(A.7)* can include squared terms to acknowledge nonlinear relationships, and interaction terms between the response variables.

We analyzed the dataset and employed factor analysis to reduce the number of explanatory variables to improve model prediction power.[6] We use these results to specify a predictive model that allows for interaction between qualitative variables was chosen as the one with the higher predictive power.[7]

[5] The model herein proposed to build upon previous work conducted by CUTR in estimating worksite trip reduction tables [30].

[6] Factor analysis is a statistical technique that reduces several variables that are correlated into a smaller set of new, uncorrelated and meaningful variables.

[7] In a regression model, qualitative variables take the form of dummy variables. These are explanatory variables that take the value of 1 if present or take the value 0 if absent. For example, dummy variables can be used to estimate main effects due to the presence or the absence of a given program promotion initiative, a given subsidy, and the offering or not of a guaranteed

A3. Land Use Controls and Transit Travel Behavior

Abstract

In recent years, urban policies intended to reduce presumed negative externalities associated with suburbanization have focused on reducing auto travel by manipulating urban form to reduce trip frequencies and travel distances. In addition, it is assumed that shorter distances provide added opportunities to link more destinations in a single trip chain. The effectiveness of sustainable transport strategies, however, provides mixed evidence. This is so because the research is based on ad-hoc empirical specifications, lacking a formal behavioral framework that considers travel the result of activities planned and executed through space and time. This study seeks to provide such a behavioral framework and test its implications empirically. We present an analytical model of the interaction between urban form and the demand for transit travel, in which residential location, transit demand, and the spatial dispersion of non-work activities are endogenously determined. Transit demand is determined by residential location, work trips, non-work trip chains, and goods consumption. Theoretically derived hypotheses are empirically tested using a dataset that integrates travel and land-use data. We find that population density does not have a large impact on transit demand and that the effect decreases when residential location is endogenous. In addition, when population density and residential location are jointly endogenous, the elasticity of transit demand with respect to walking distance to a transit station decreases by about 33 percent over the case in which these variables are treated an exogenous. We find that households living farther from work use less transit and that trip-chaining behavior explains this finding. Households living far from work engage in complex trip chains and have, on average, a more dispersed activity space, which requires reliance on more flexible modes of transportation. Therefore, reducing the spatial allocation of non-work activities and improving transit accessibility at and around subcenters would increase transit demand. Similar effects can be obtained by increasing the presence of retail locations in proximity to transit-oriented households. Although focused on transit demand, the framework can be easily generalized to study other forms of travel.

Motivation

Despite a significant amount of academic and practitioner-oriented research, the practice of choosing the right transit service to support desired development and the right development to support transit ridership relies on findings that no longer apply to the current urban landscape. Early studies estimated the housing and job densities necessary to support different transit modes [44]. Such studies did not consider changes in urban structure, such as transit-oriented development, that have recently emerged. At the same time, the urban landscape has evolved from monocentricity, where the CBD is the predominant employment center, to polycentricity, where multiple employment centers characterize an urban area and where households can locate anywhere in an increasingly suburban environment. Employment decentralization, coupled with the increased relevance of non-work travel, has had a profound impact on the way transit responds to urban form, making the earlier studies obsolete.

ride home program. Furthermore, very often these initiatives are linked to each other in an interactive fashion. An interaction model has to be built to analyze a main effect model.

Debate has shifted from the need to determine minimum density thresholds that support transit to the need to provide reliable information to guide decision makers about what mix of land-use policies would better promote transit use. In most previous work, density is treated as exogenous and is assumed not to be impacted by transportation system changes. It is now recognized that this approach is inadequate and that what is needed is an empirically estimable behavioral model conducive to generalization and applicability.

Among the challenges posed by evolving trends in transport and land-use is providing a better explanation of the role of non-work travel in residential location decisions. Greater mobility and a shift from monocentric to polycentric urban forms have substantially increased non-work travel, further weakening the relevance of the classical commuting-based theory of residential location [45].

Although the transportation literature on non-work travel has grown in recent years, it has largely done so without providing a generally accepted behavioral framework. Recent attempts to unify the economic theory of urban residential location and transportation highlight the relevance of non-work travel to residential location [46, 47]. Central to this endeavor is the notion that in choosing a residential location, the household considers the pattern of non-work trips that its members are likely to make from that residential location. Accessibility to non-work opportunities is likely to be important and, for many households, perhaps more important than accessibility to jobs. In addition, the extent to which households self-select into communities that support their preferences for transportation and other amenities complicates the effort to uncover causality between urban form and travel behavior.

Research Objectives

The objectives of this paper are to (1) define a theoretical model of the interaction between urban form and the demand for transit, in which residential location, transit demand, and the spatial dispersion of non-work activities are endogenously determined, and (2) to test the hypotheses of that model.

The research:

1. Controls for idiosyncratic preferences toward residential location to test the hypothesis that land-use characteristics affect non-work travel behavior.
2. Shifts the focus from monocentric measures of urban form to polycentric ones.
3. Utilizes a framework that better accounts for the influence of space on travel patterns, by shifting the focus from a single-purpose trip-generation analysis to one that accounts for scheduling and trip-chaining effects.
4. Accounts for the trade-off between commute time and non-work activities.

Summary and Implications for Integrated Models of Transportation and Land Use

There is a vast body of literature on the relationship between travel and urban form (for a review see for example, Crane [48], Boarnet and Crane [49], Badoe and Miller [50], and Ewing and Cervero [51]).

Most of the work is empirical in nature and is based on the application of multivariate techniques that regress various measures of travel behavior (commute length, vehicle-miles of travel, mode choice) on measures of residential and employment density, while controlling for the demographic characteristics of travelers. These studies examine the statistical significance, sign, and magnitude of the estimated coefficient on residential population density or employment density. A statistically significant negative coefficient leads one to conclude that a negative relationship exists between travel and density. For example, higher density leads to shorter commutes, fewer vehicle-miles of travel (VMT), or a shift from auto transportation to alternative modes, such as transit. The abundance of these types of studies has led to the conclusion that policy interventions directed to influence density are capable of reducing automobile use.

A comprehensive literature review uncovered the following issues that, to date, have been addressed but not completely resolved. In particular, it is widely recognized that there is a lack of a behavioral framework that can be applied to empirical work and is conducive to generalization of findings and applicability. Studies that relate density (population and employment) measures to travel behavior are monocentric and, therefore, fail to account for the employment and residential decentralization now characterizing the urban landscape. In most of this work, density is treated as exogenous and is not assumed to be impacted by transportation system changes. These studies have undergone systematic criticism due to their ad-hoc specifications and because of omitted variable bias problems due to the possibility that the relationship between urban form and travel might entail simultaneity and endogeneity. In addition, most of the work that jointly estimate transit demand, transit supply, and factors affecting both supply and demand are affected by methodological faults, ranging from misuse of simultaneous equation modeling methods to improper functional specifications.

More recent developments in travel demand behavior and geographical science provide some insight on how better to capture the relationship between urban form and travel in a highly decentralized context. The significance of the CBD in determining transit ridership levels has been revisited and more relevance is now attributed to decentralized employment by examining the influence of subcenters in an increasingly polycentric urban landscape.

While early work sought to provide a generalized analytical framework that made use of aggregate data, the more recent literature consists of papers that model the simultaneous decision of location and travel (as an application of improved discrete-choice modeling techniques) in a context where individuals choose locations based on specific travel preferences (for example, a preference about a specific mode) at the disaggregate level. Location decisions based on idiosyncratic preferences for travel define the term “residential self-selection behavior” to indicate how individuals with similar tastes and preferences tend to cluster together in given locations.

Finally, there is a lack of empirical work that studies the relationship between urban form and travel behavior within an activity-based framework, which takes into account the complexity of travel (i.e., that accounts for trip chaining). Those studies that have employed activity-based modeling have failed to properly account for endogeneity and have disregarded spatial mismatch effects. In examining the relationship between urban form

and travel, it is crucial to distinguish the effects of land use from the effects of systematic socio-demographic differences of individuals.

It is the purpose of this dissertation to provide an estimable model for these failings of previous research.

Behavioral Model

Following the methodological issues highlighted by the literature review, the proposed framework seeks to address unresolved issues as follows:

- It controls for individual idiosyncratic preferences for residential location
- It shifts the focus from monocentric-based measures of urban form to polycentric ones
- It utilizes a framework that better accounts for the spatial influence on travel patterns, by shifting the focus from a single-purpose trip-generation analysis to one that accounts for trip chaining
- It accounts for the trade-off between commute time and non-work activities

In this model, travel demand is considered a derived demand brought about by the necessity to engage in out-of-home activities whose geographical extent is affected by urban form. Furthermore, budget-constrained utility-maximizing behavior leads to an optimization of the spatiotemporal allocation of these activities and an optimal number of chained trips. Socio-demographic factors directly influence residential location, consumption, and travel behavior.

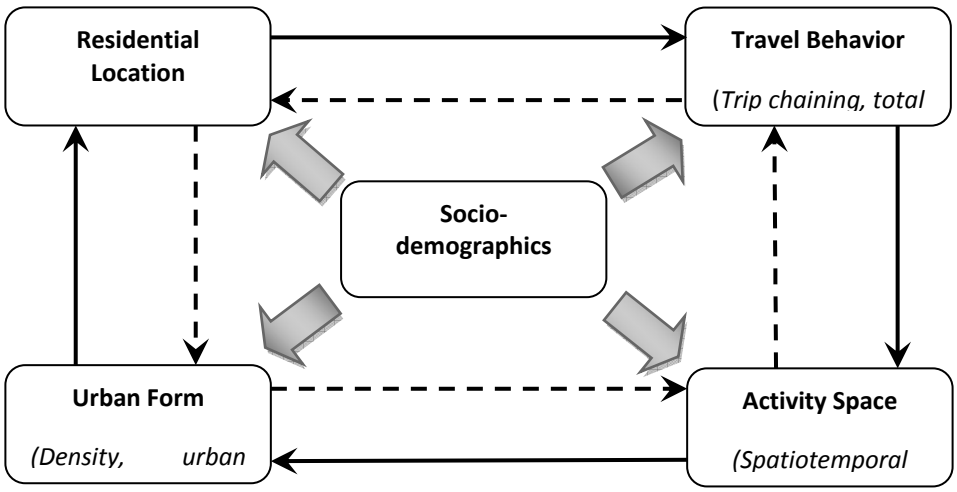

FIGURE A.1 Conceptual Model of Urban Form and Travel Behavior

In this model, residential location, travel behavior, the activity space, and urban form are all endogenously determined. Following urban residential location theory, the location decision is assumed to be the result of a trade-off between housing expenditures and transportation costs, given income and the mode-choice set. In a departure from the monocentric model, the definition of residential location is taken from the polycentric model

of Anas and his associates [52, 53]. In this work, residential location is defined as the optimal *job-residence pair* in an urban area in which jobs and residences are dispersed. Following Anas [46], the location decision is also based on idiosyncratic preferences for location and travel. In addition to determining optimal residential location, this approach also determines the optimal sequence of non-work trip chains, goods consumption, and transit patronage. It is within this framework that questions related to the interrelation between urban form, residential location, and transit travel demand are addressed. How do location decisions affect travel behavior? How does urban form relate to travel behavior? Do residential location and urban form affect travel behavior? What is the impact of higher density on travel behavior? To address these questions, we first introduce a basic travel demand model treating residential location and density as exogenous (Model I). We then consider subsequent extensions (Model II and Model III) that relax these assumptions to discuss what expected behavioral conclusions can be reached.

Model I: Exogenous Residential Location and Density

In this specification, residential location, transit station proximity, and density are exogenous. Given these variables, the model jointly defines the activity space and the optimal trip chain. The joint determination of activity space and trip chain determines a travel demand function, given consumption and location decisions. The household (rather than the individual) is the unit of analysis because these decisions take place at the household level. Empirical studies on the relevance of transit station proximity to transit patronage show a strong relationship between transit use and station proximity [54, 55]. Therefore, this model includes this possibility. To include these considerations, Model I takes the following specific form

$$TC = TC(AS, RL, WD, X_{TC}) \tag{3.1}$$

$$AS = AS(TC, D, X_{AS}) \tag{3.2}$$

$$TD = TD(TC, AS, RL, WD, X_{TD}) \tag{3.3}$$

where

TC = the number of non-work trip stops per commute-chain or chain length

AS = the activity space (measured as the geographic area surrounding the residence in which non-work trips are made)

TD = the demand for transit trips (measured as the number of transit trips)

RL = residential location (measured as the *job-residence pair* distance)

D = a vector of residential and employment density controls

WD= transit station proximity (measured as walking distance to the nearest transit station)

X_{TC} = a vector of controls specific to the *TC* function;

X_{AS} = a vector controls specific to the *AS* function

X_{TD} = a vector of controls specific to the TD function

This model permits testing the hypothesis that individuals living farther from the workplace engage in more complex tours characterized by a higher number of non-work trips linked to the commute tour. As in Kondo and Kitamura [56], the number of non-work trip stops, *TC*, determines the length of the trip chain. In addition, *TC*, as it relates to transit patronage, is directly affected by transit station proximity and by other factors summarized by the vector of controls, $X_{TC.}$ This vector, as explained in more detail in Chapter 4, includes vehicle availability and the presence of young children among other factors likely to affect trip-chaining formation.

Trip-chaining behavior defines an activity space, *AS*, which is assumed to represent the optimized spatiotemporal allocation of non-work activities as affected by the built environment, summarized by the exogenous vector, D. For example, more densely populated urban areas have more densely clustered activity locations, which shrink the size of the activity space relative to less densely populated areas. A smaller activity space reduces trip chaining, *TC*, ultimately affecting the demand for travel, *TD*. As we shall see, *AS* captures the characteristics of activity locations as well as the spatiotemporal constraints linked to trip-chaining behavior.

This model is suited to either describe a situation where residential location is considered as predetermined, such as a short run time frame or can be used to cross compare decision making among households at any point in time. The model may be used to test the effect of urban design policies directly affecting travel distances and the land-use mix. Specifically, it may be used to test if higher density environments entail shorter travel distances, which in turn should affect the composition and complexity of trip chains and the overall amount of travel.

Residential Location, *RL,* and Transit Station Proximity, *WD*

The definitions of residential location and transit station proximity used here differ from those used in the current literature. For example, in studies of residential self-selection, the location decision is often presented as a dichotomous choice, i.e., whether to live near or far away from a transit station. Proximity is measured by a circular buffer around a station, often with a half-mile radius. The extent of this buffer is usually justified on empirical grounds. Cervero [54], for example, used a half-mile radius in estimating a nested logit model of the joint determination of mode and location. This measure of transit proximity fails to account for barriers that prevent access to a station that lies within the half-mile radius. Some researchers have considered residential location as a choice to reside within a geographical unit, such as a traffic assignment zone [57, 58].

The use of transit proximity as a proxy for residential location, while dictated by the need to sort out the influence of the built environment from self-selection, is not based on any other theoretical underpinnings about the decision-making process that is at the heart of urban residential location theory. That is, it does not take into consideration the trade-off between housing and transportation costs that, at the margin, determine where an individual decides to locate. For example, the standard theory of location shows that individuals choose an optimal distance between work and home given housing and transportation costs. In a monocentric model that only looks at travel between home and the CBD, individuals locate at a distance where the marginal cost of transportation is equal to the marginal housing cost savings obtained by a move farther from the CBD [59, 60]. Recent departures from this view consider that individuals can locate anywhere in an urban area, choosing an optimal home-work distance that optimizes also the amount of non-work travel and non-work activities [52, 53]. Further explorations also consider the role of trip chaining behavior [46].

Activity Space: Spatial Dispersion of Non-Work Activities

The concept of activity space, although not new to behavioral sciences, is novel in terms of its application to travel behavior. The relationship between urban form and geographical patterns of activities has been studied only recently, due to the availability of specialized travel diary data and increasingly sophisticated geospatial tools. A growing field of research that looks at the relationship between urban form and the spatiotemporal allocation of activities and travel provides additional insight on the impact of the built environment. Recent research describing travel behavior and the influence of urban morphology and entire patterns of daily household activities and travel demonstrates how households residing in decentralized, lower density, urban areas tend to have a more dispersed activity-travel pattern then their counterpart residing in centralized, high density urban areas [61, 62].

This study explicitly accounts for the influence of the built environment in affecting the spatial dispersion of activities and how spatial dispersion affects the demand for travel and location decisions. This effect is accounted for by introducing the variable *activity space*, *AS,* into the model. The extent of the activity space is assumed to be affected by the built environment. Densely populated urban areas tend to cluster activity locations together thus shrinking the size of the activity space. This affects the spatial allocation of activities, thus affecting the demand for travel. As seen in the next chapter, there exist several ways empirically to measure the spatial dispersion of activities.

Trip Chaining, TC

According to activity-based modeling practice, trip chaining describes how travelers link trips between locations around an activity pattern. In this context, a trip from home to work with an intermediate stop to drop children off at day care is an example of a trip chain. In the literature there is not a formal definition of *trip chain,* and different terms and expectations exist as to what kind of trips should be considered as part of a chain [63]. Sometimes, the term *trip chain* is used interchangeably with the term *tour* to indicate a series of trips that start and end at home.

In this study, we hypothesize that trip chaining occurring on the home-job commuting pair saves time. These time savings in turn can be either allocated to additional non-work travel, thus increasing the overall demand for travel (e.g., total number of trips), or be used to determine a longer commute (i.e., a home-job commuting pair farther apart). The hypothesis of increased discretionary travel due to trip-chaining has recently been theoretically demonstrated [46]. The hypothesis of a positive relationship between more complex trip chains and the home-work commute is confirmed by empirical work. For example, in an analysis of trip chaining involving home-to-work and work-to-home trips using data from the 1995 nationwide personal transportation survey (NPTS), McGucking and Murakami [63] found that people are more likely to stop on their way home from work, rather than on their way to work. About 33 percent of women linked trips on their way to work compared with 19 percent of men, while 61 percent of women and 46 percent of men linked trips on their way home from work. Using the 1991 Boston Household Travel Survey, Bhat [64] found that about 38 percent of individuals made stops during the commute trip. Davidson [65] found similar results from her analysis of commute behavior in a suburban setting, showing that travelers rely heavily on trip chaining in an urban context characterized by higher spatial dispersion of non-work activities. Other studies also provide empirical evidence of increased stop-making

during the commute periods [66] or how the ability to link trips is enhanced by the flexibility inherent in automobile use [67].

Travel Demand, TD

Travel demand is herein treated as a derived demand brought about by the need to purchase goods and services. Travel demand, *TD*, measures the number of work and non-work transit trips at the household level. The decision process behind the choice of the number of trips, as formalized by this framework, considers trip generation as a function of trip chaining and exogenous residential location and socio-demographic factors. The constrained maximization problem of the joint determination of activity space and trip-chaining defines an optimal vector of non-work trips, given residential location and urban form characteristics (e.g., residential and employment density levels, land-use mix). This treatment of travel demand as derived from the desire to engage in out-of-home activities departs in terms of behavioral sophistication from the treatment of trip generation as developed by Boarnet and Crane [49] in their analysis of travel demand and urban design. In Boarnet and Crane [49] trip demand functions are either directly affected by land use or indirectly (by influencing the cost of travel).

In contrast, in this model land use (i.e., urban form) directly affects the spatial allocation of activities. As shown by Anas, [46], it is the budget-constrained utility-maximization behavior that defines optimal travel patterns. The complexity of this mechanism is better shown in the ensuing comparative static analysis, which allows ascertaining the effect that urban form exerts on the demand for travel.

Comparative Static Analysis

The basic theoretical implications of Model I can be explored by employing comparative static analysis. This section considers the impact of changes in exogenous density, D and exogenous residential location, RL, on travel demand, *TD*. Basically, starting from an equilibrium state, the impacts of an increase in density and residential location on the initial equilibrium are determined. The objective is to see what happens to transit demand as density levels change (for additional details on assumptions and derivation of the comparative statics, see Appendix A).

Effects of an Increase in Density, D

The effect of an increase in density on travel demand is obtained as

$$\frac{dTD}{dD} = \frac{\overbrace{\overbrace{TD_{AS}}^{(-)}\overbrace{AS_D}^{(-)}}^{\alpha} + \overbrace{\overbrace{TD_{TC}}^{(-)}\overbrace{TC_{AS}}^{(+)}\overbrace{AS_D}^{(-)}}^{\beta}}{\underbrace{1-\underbrace{AS_{TC}}_{(-)}\underbrace{TC_{AS}}_{(+)}}_{(+)}} > 0 \qquad (3.4)$$

where subscripts denote a partial differentiation of the subscripted variable with respect to the variable abbreviated by the subscript. The product $\alpha = TD_{AS}AS_{TD}$ gives the increase in transit demand caused by a contraction in the activity space as a result of increased density. The product $\beta = TD_{TC}TC_{AS}AS_D$ gives the increase in transit demand caused by decreasing trip chaining as a result of increased density

Based on an assumed relationship between spatial dispersion of activities and trip chaining, the result of this analysis shows that changes in density levels exert two contrasting effects on the demand for transit trips.

This explanation is inherent in the determinants of trip chaining behavior. In higher density environments, as the spatial extent of non-work activities reduces, trip chaining needs decrease, but individual trips increase and individuals prefer to make non-chained trips. First, increased density reduces the activity space, which directly increases the demand for non-chained trips. Second, increased density reduces the activity space, which reduces the need to chain trips (as time-saving opportunities decrease) and thus the demand for transit trips.

Change in Residential Location, RL

Next, we derive the comparative statics of an increase in residential location, *RL*. Note that *RL* is considered as predetermined in Model I. The question to be answered is: "What happens to transit demand as the job-residence pair changes?" Using cross sectional data, this question can be translated as: "How does transit demand differ for those households facing long commutes from those making short commutes?"

The comparative static result describing the impact of a change in residential location on the demand for transit trips is

$$\frac{dTD}{dRL} = \frac{\overbrace{TD_{RL}}^{(\pm)} + \overbrace{TC_{RL}}^{(+)}\overbrace{TD_{TC}}^{(-)} + \overbrace{AS_{TC}}^{(-)}\left(\overbrace{TC_{RL}}^{(+)}\overbrace{TD_{AS}}^{(-)} - \overbrace{TC_{AS}}^{(+)}\overbrace{TD_{RL}}^{(\pm)}\right)}{\underbrace{1-\underbrace{AS_{TC}}_{(-)}\underbrace{TC_{AS}}_{(+)}}_{(+)}} \gtrless 0 \qquad (3.5)$$

As previously discussed, an increase in residential location increases trip chaining ($TC_{RL} > 0$), which in turn positively affects both the size of the activity space, *AS*, and the demand for transit services. The overall effect on transit demand hinges on the sign of TD_{RL}. To the extent that an urban area is well served by transit, then the relationship between transit demand and residential location is positive. A positive relationship is observed in older, more monocentric cities, where existing transit services support commuting. On the other hand, if supply

constraints exist, transit demand declines as the job-residence distance increases. Therefore, the overall effect on transit demand due to a change in location depends on both the sign and magnitude of TD_{RL}.

Change in Walking Distance to Nearest Station, WD

A change in transit station proximity causes a change in transit demand equivalent to

$$\frac{dTD}{dWD} = \frac{\overbrace{TD_{WD}}^{(-)} + \overbrace{TD_{TC}}^{(-)}\overbrace{TC_{WD}}^{(\pm)} + \overbrace{AS_{TC}}^{(-)}\left(\overbrace{TC_{WD}}^{(\pm)}\overbrace{TD_{AS}}^{(-)} - \overbrace{TC_{AS}}^{(+)}\overbrace{TD_{WD}}^{(-)}\right)}{\underbrace{1 - \underbrace{AS_{TC}}_{(-)}\underbrace{TC_{AS}}_{(+)}}_{(+)}} \lesseqgtr 0 \qquad (3.6)$$

The overall effect of an increase in walking distance is ambiguous. An increase in distance to the nearest station directly reduces transit demand ($TD_{WD} < 0$). At the same time, reduced accessibility impacts and the ability to engage in trip chaining using transit, producing an ambiguous effect on transit demand. The sign hinges on the relationship between trip chaining and distance to the nearest transit station, ($TC_{WD} \gtreqless 0$), which is undetermined. On the other hand, the empirical literature provides unequivocal evidence of a negative relationship between distance to transit stops and the demand for transit services [54, 68]. The debate is mostly centered on the magnitude of this relationship, as high-lighted by the growing body of literature on residential self-selection.

Model II: Endogenous Residential Location, Exogenous Density

In this model, we relax the assumption of exogenous residential location. Treated as a choice variable, residential location is the outcome of a trade-off between transportation and housing costs. Taking into account idiosyncratic preferences for location, households choose an optimal home-work commute pair, while at the same time optimizing goods consumption and the ensuing non-work travel behavior (optimal non-work trip chaining and activity space). This model is specified as

$$TC = TC(AS, RL, WD, X_{TC}) \qquad (3.8)$$

$$AS = AS(TC, D, X_{AS}) \qquad (3.9)$$

$$TD = TD(TC, AS, RL, WD, X_{TD}) \qquad (3.10)$$

$$RL = RL(TC, TD, X_{RL}) \qquad (3.11)$$

where X_{RL} is a vector of controls specific to the RL equation and all other variables are as defined earlier.

Comparative Static Analysis

The complete comparative statics are presented in Appendix B. A discussion of the findings is presented below. Note that the inclusion of the endogenous residential location equation, *RL*, complicates the computation of the total partial derivatives.

Effects of an Increase in Density, D

The effect of an increase in density on travel demand is obtained as

$$\frac{dTD}{dD} = \frac{\overbrace{AS_D}^{(-)}\left[\left(1-\overbrace{RL_{TC}}^{(+)}\overbrace{TC_{RL}}^{(+)}\right)\overbrace{TD_{AS}}^{(-)}+\overbrace{TC_{AS}}^{(+)}\left(\overbrace{RL_{TC}}^{(+)}\overbrace{TD_{RL}}^{(\pm)}+\overbrace{TD_{TC}}^{(-)}\right)\right]}{\underbrace{1-\underbrace{RL_{TC}}_{(+)}\underbrace{TC_{RL}}_{(+)}-\underbrace{RL_{TD}}_{(\pm)}\underbrace{TD_{RL}}_{(\pm)}+\underbrace{AS_{TC}}_{(+)}\left[-\underbrace{RL_{TD}}_{(\pm)}\underbrace{TC_{RL}}_{(+)}\underbrace{TD_{AS}}_{(-)}+\underbrace{TC_{AS}}_{(+)}\left(-1+\underbrace{RL_{TD}}_{(\pm)}\underbrace{TD_{RL}}_{(\pm)}\right)\right]-\underbrace{RL_{TD}}_{(\pm)}\underbrace{TC_{RL}}_{(+)}\underbrace{TD_{TC}}_{(-)}}_{|J|}} \lesseqgtr 0 \qquad (3.12)$$

In the long run, the activity space, transit demand, trip chaining and residential location are all jointly determined. Exogenous changes in density levels therefore affect all these variables. An increase in density directly contracts the activity space, whereas it indirectly reduces trip chaining and ambiguously affects transit demand through its effect on the activity space. The effect on residential location operates through the effect on transit demand, but that effect is ambiguous. This renders the effect of density on transit demand ambiguous as well. Comparing equation (3.12) to equation (3.4), we see that the complexity of the relationship between transit demand and density increases substantially.

Change in Walking Distance to Nearest Station, WD

The comparative static effect of a change in transit station proximity on transit demand is

$$\frac{dTD}{dWD} = \frac{\overbrace{TD_{WD}}^{(-)}+\overbrace{\overbrace{TD_{TC}}^{(-)}\overbrace{TC_{WD}}^{(\pm)}}^{\pm}+\overbrace{RL_{TC}}^{(+)}\left(\overbrace{\overbrace{TC_{WD}}^{(\pm)}\overbrace{TD_{RL}}^{(\pm)}-\overbrace{TC_{RL}}^{(+)}\overbrace{TD_{WD}}^{(-)}}^{(\pm)}\right)+\overbrace{AS_{TC}}^{(+)}\left(\overbrace{\overbrace{TC_{WD}}^{(\pm)}\overbrace{TD_{AS}}^{(-)}-\overbrace{TC_{AS}}^{(+)}\overbrace{TD_{WD}}^{(-)}}^{(-)}\right)}{|J|} \lesseqgtr 0 \qquad (3.12)$$

With endogenous residential location, the sign, as well as the magnitude of dTD/dWD depends on both the sign and magnitude of TD_{RL} and TC_{WD}, all of which are unknown. As in Model I, the effect of *WD* is ambiguous.

Model III: Endogenous Residential Location, Endogenous Density

In this last extension to Model I, the assumption of exogenous density is relaxed. This model translates the conceptual framework of Figure 3.1 into the following analytical model

$$TC = TC(AS, RL,\ WD, X_{TC}) \qquad (3.13)$$

$$AS = AS(TC, D, X_{AS}) \qquad (3.12)$$

$$TD = TD(TC, AS, RL, WD, X_{TD}) \qquad (3.13)$$

$$D = D(RL, AS, X_D) \qquad (3.14)$$

$$RL = RL(TC,, X_{RL}) \qquad (3.15)$$

In the long run, the simultaneous choice of location and travel decisions is assumed to affect density levels across a given urban area. This model best describes a long-run equilibrium, in which both location and travel decisions are optimized under constraint. Urban form is treated as endogenous to the process and is itself affected by household travel decisions and location behavior. Aspects of this relationship and its influences on transit

patronage have been previously considered in the literature. For example, while modeling long-run transit demand responses to fare changes, Voith [69] treats density as endogenous and being affected directly by transit patronage levels. In the long run, these levels are affected by supply-side changes. Voith [69] assumes that as transit services improve, more people tend to live in proximity to transit stations, thus increasing the demand for transit services.

Ideally, empirical testing of this model would rely on panel data of individual travel diaries. Generally, however, panel data are unavailable and cross-section data are relied on. With cross section data, we can study changes in behavior by controlling for individual heterogeneity.

Comparative Static Analysis

Given the endogenous treatment of density, we can use this model to test the effects of policies geared at directly affecting density, such as policy interventions intended to increase density around transit stations. Assuming an exogenous shock, θ, positively affecting density, comparative statics can be obtained. The inclusion of two more equations complicates the calculations to derive the relevant comparative static results. The results are basically the same as Model II, although the expected magnitudes of impacts differ. To avoid cluttering the text, Appendix A reports the comparative statics results, which we will use in the empirical work of Chapter 4. Table 3.1 reports a summary of the comparative statics highlighting the expected signs from changes in the most relevant variables affecting trip chaining, *TC*, activity space, *AS*, and transit demand, *TD*.

TABLE 3.1 Comparative Static Results

Exogenous Variable	*D*	*RL*	AS_{φ}^{*}	TC_{φ}^{*}	*WD*
Effect on Trip Chaining, *TC*	-	+	+	+	+/-
Effect on Activity Space, *AS*	-	+	+	-	+/-
Effect on Transit Demand, *TD*	+	+/-	-	-	+/-

*Shift parameters affecting *AS* and *TC*

The analytical framework we presented above seeks to strike a balance between the complexity of activity-based modeling and the more traditional discrete-choice frameworks. The added complexity of the models introduced here is intrinsic to the explicit consideration of non-work travel behavior and its interrelationship with the spatial extent of non-work activities.

These analytical models are general and can be applied to data from any urban area. Empirical testing of the hypotheses of these models requires detailed travel behavior data at the individual level. The increased level of sophistication of activity-based travel diaries allows collecting information on activities conducted at home and out of home, as well as their spatial location. As we shall see, the contribution of geographic information system (GIS) modeling permits the measurement of the geographic dimension of both activities and travel and relating

them to the surrounding urban landscape. Coupling GIS with econometric modeling allows conducting empirical tests of the relationships generated by the models of this chapter.

Empirical Analysis

Data Sources

To test the models presented we use travel-diary data from the 2000 Bay Area Travel Survey (BATS2000). BATS2000 is a large-scale regional household travel survey conducted in the nine-county San Francisco Bay Area of California by the Metropolitan Transportation Commission (MTC). Completed in the spring of 2001, BATS2000 provides consistent and rich information on travel behavior of 15,064 households with 2,504 households that make regular use of transit.[8] In the dataset, 99.9 percent of home addresses and 80 percent of out-of-home activities were geocoded using geographic information systems (GIS) to the street address or street intersection level (99.5 percent to the street address level). This permits a precise geographic determination of non-work activities, job, and residential unit locations.

The choice of this dataset goes beyond its quality. Most of the relevant academic and practitioner work on the relationship between transit and urban form, research on the issue of residential self-selection, and the efficacy of transit-oriented development policies (TOD) made use of BATS2000 [70]. . Most of the work we reviewed in this paper used this dataset.

The final dataset combines BATS2000 travel behavior data with geographical data from the Census Bureau Summary File 3, which consists of detailed tables of social, economic, and housing characteristics compiled from a sample of approximately 19 million housing units (about 1 in 6 households) that received the Census 2000 long-form questionnaire [71]. We obtained these data at the Census block-group level. Thus, we measure housing and neighborhood characteristics at the block-group level where the residential unit is located.

The unit of observation is the household to reflect the higher hierarchical decision making process of both residential location and travel needs. Referring to MTC work on transit use and station proximity [72], a transit household is defined as one where one or more members used transit at least once during the two-day surveying period.

Dependent Variables Descriptive Statistics

Measures of Activity Space, *AS*

Activity space measures the spatial dispersion of non-work activity locations. Non-work activities consist of shopping, recreational activities (e.g. visiting friends or dining out), and non-recreational activities (doctor visits, child rearing, recurring activities). These activities can be located in proximity to the household residential unit or be located away from it. To measure the spatial extent of these activities across the urban landscape, we employ area-based geometric measures developed in transportation geography. Different metrics that describe the

[8]MTC defines a transit household as one where one or more members used transit at least once during the two-day surveying period.

spatial extent of activity locations can be employed. The simplest measure is represented by the standard distance circle (SDC) (or standard distance deviation), which is essentially a bivariate extension of the standard deviation of a univariate distribution. It measures the standard distance deviation from a mean geographic center and is computed as

$$SDC = \sqrt{\frac{\sum(x_i-\bar{x})^2+\sum(y_i-\bar{y})^2}{n}} \tag{4.1}$$

where $\bar{x}$ and $\bar{y}$ represent the spatial coordinates of the mean center of non-work activities at the household level, and the *i* subscript indicates the coordinates of each non-work activity. The mean activity center is analogous to the sample mean of a dataset, and it represents the sample mean of the *x* and *y* coordinates of non-work activities contained in each household activity set. The coordinates represent longitude and latitude measurement of each activity and are reported in meters following the Universal Transverse Mercator (UTM) coordinate system. Household activity locations are those visited by surveyed household members during a specified time interval, in this case two representative weekdays. Thus, the standard distance of a household's activity pattern is estimated as the standard deviation (in meters or kilometers) of each activity location from the mean center of the complete daily activity pattern. Interpretation is relatively straightforward, with a larger standard distance indicating greater spatial dispersion of activity locations. The area of the SDC is the area of a circle with a radius equal to the standard distance. The SDC provides a summary dispersion measure that can be used to explore systematic variations of activities subject to socio-demographic, travel patterns, and patterns of land-use.

As pointed out by Ebdon [73], this measure is affected by the presence of outliers or activities that are located farthest from the mean center. As a result of the squaring of all the distances from the mean center, the extreme points have a disproportionate influence on the value of the standard distance. To eliminate dependency from spatial outliers, another measure of dispersion, called the standard deviational ellipse (SDE) is usually employed, which uses an ellipse instead of a circle. The advantages of the SDE with respect to the SDC have been discussed in the literature [73]. In addition to control for outliers, the SDE also allows accounting for directional bias of activities with respect to their mean center. The ellipse is centered on the mean center with the major axis in the direction of maximum activity dispersion and its minor axis in the direction of minimum dispersion (See Figure 4.1). In this study, we employ the standard distance ellipse (*SDE*), using the formula described in Levine [74]

$$SDE = \sqrt{\frac{\sigma_x^2+\sigma_y^2}{2}} \tag{4.2}$$

where σ_x and σ_x represent the length of the major and minor axes of the ellipse.

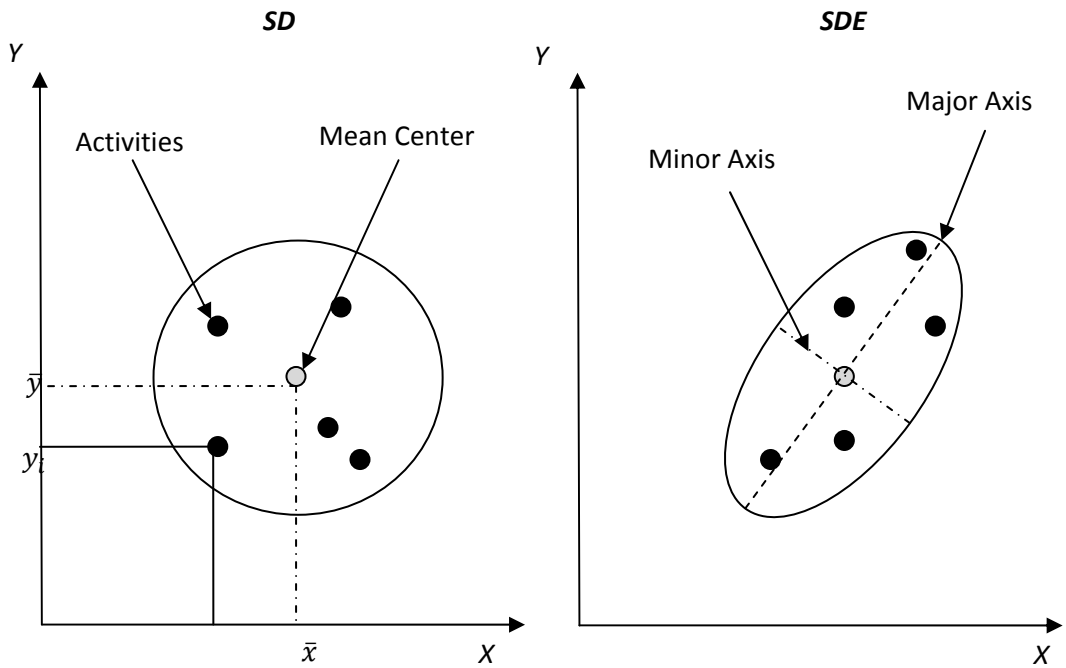

FIGURE 4.1 Standard Distance Circle and Standard Distance Ellipse

Measures of Residential Location, RL

We define residential location as the average distance of household employment activities to the household residential unit

$$RL = \frac{\sum_{m=1}^{k} dist_{mj}}{k} \tag{4.3}$$

where $dist_{mj}$ is the Euclidean distance to the residential unit located at *j*, from a household member work location *m*, and *k* is the total number of employed household members. An alternative specification only considers the distance between the household head's work location and the residential unit. This assumes that the residential location choice puts more relevance to the location of the household "breadwinner," as discussed in detail later in this chapter.

Measures of Transit Station Proximity, WD

In this study, we treat transit proximity as a continuous variable measuring distance to the nearest transit station from the household residential unit. A 2006 publication from MTC made use of BATS2000 data to look at the relationship between transit use, population density, and characteristics of individuals living near transit stations [72]. An appendix to this study was recently published on the MTC website which reports an updated version of the household file containing an additional variable measuring network walking distance from each household residential unit to the nearest transit station [75]. Using this file, we measure walking distance as actual distance based on network characteristics to take into consideration the existence of accessibility impediments.

Measures of Density, D

We measure the dependent variable density, *D*, as gross population density of the Census block group in which the household residential unit is located. The Census block-group area is measured in square miles. As discussed in Chapter 2, other studies on transit and urban form tend to utilize number of dwelling units per square mile. We also consider additional urban form measures, initially treated as exogenous to the model, which we describe under the exogenous variable section of this chapter.

Table 4.1 presents basic descriptive statistics of the dependent variables, split by different gross population density levels corresponding to the classification adopted by MTC to differentiate between urbanized and non-urbanized areas. As documented in Chapter 2, there exists an underlying correlation between density levels and travel behavior. This table shows how the activity space is slightly larger for transit households than for non-transit households (19.1 versus 17.2 square miles) and contracts as density increases, while trip chaining does not follow this linear relationship. Walking distance to the nearest station noticeably decreases at higher density levels. To highlight the relevance of transit patronage, Table 4.2 compares sample transit trip averages to auto, walk and other trips. This table shows marked differences in terms of trip making and trip chaining behavior between transit and non-transit households, as well as in average travel times between home and work between transit and non-transit households (51.9 minutes versus 37.4 minutes).

Explanatory Variables Descriptive Statistics

Socio-Demographic Variables

We treat the following socio-demographic variables as exogenous explanatory variables:

- Household characteristics
- Householder gender
- Householder race
- Number of children of school age
- Number of persons employed full-time
- Household income
- Number of vehicles
- Number of licensed individuals
- Tenure (own versus rent)

These variables are available from the BATS2000 person file. Some of these socio-demographic variables have been included in the studies reviewed in Chapter 3 dealing with the influence of land use on transit patronage, while the most current literature on self-selection considers all of them. Table 4.3 provides a summary of these variables for the overall sample. As with the vast majority of travel survey, the white population is overly represented, as well as the higher income groups.

TABLE 4.2 Descriptive Statistics: Sample Means of Dependent Variables and Selected Trip Measures

Transit Household		*Gross Population Density (persons/mile^2)*	*Household Activity Space (mile^2)*	*Residential Location, RL (miles)*	*Residential Location, RL (min)*	*Trip Chaining, TC (number)*	*Transit Trips (number)*	*Auto Trips (number)*	*Walk Trips (number)*	*Walking Distance, WD (mile)*
No	Mean	7,910.51	17.16	10.33	37.36	2.87	-	8.32	0.73	0.49
	SD	8,752.95	38.40	10.07	33.32	1.77	-	6.14	1.62	1.44
	N	12,260	10,548	9,128	8,353	11,242	12,260	12,260	12,260	12,260
Yes	Mean	15,172.65	19.14	11.58	51.92	3.65	2.32	5.96	1.70	0.22
	SD	17,193.12	37.84	9.76	35.35	1.73	1.29	5.77	2.38	0.38
	N	2,503	2,176	2,138	1,918	2,446	2,503	2,503	2,503	2,503
Overall Sample	Mean	9,141.78	17.50	10.57	40.08	3.01	0.39	7.92	0.89	0.45
	SD	11,006.88	38.31	10.03	34.18	1.79	1.02	6.14	1.81	1.33
	N	14,763	12,724	11,266	10,271	13,688	14,763	14,763	14,763	14,763

Data Source: 2000 Bay Area Travel Survey (BATS2000) and 2000 Census Summary File 3, Census Bureau

Travel Behavior Variables

We also created additional explanatory variables at the household level to control for factors affecting both the spatial extent of non-work activities and the ensuing travel behavior:

- Activity travel time
    - mean travel time to shopping trips starting at home
    - mean travel time to recreational trips starting at home
    - mean travel time to school trips starting at home
    - mean travel time to other trips not starting at home
    - mean travel time across all non-work activities
- Activity duration
    - mean time duration across all non-work activities

These variables are commonly used in the activity-based literature in modeling activity duration and scheduling [64, 66, 76] and activity travel patterns [77]. Transit households spend less time shopping compared to non-transit households (28.9.0 versus 30.3 minutes), they also spend less time on recreational activities (161.9 versus 175.9 minutes) and at home (181.8 versus 210.1 minutes). The time spent travelling to reach out-of-home activities also differs, with transit households spending an average of 15.7 minutes on the road versus 12.9 minutes for non-transit households. The trade-off between leisure and work is also reflected in less time spent sleeping (243.6 versus 249.6 minutes for non-transit households). These time-use variations and the comparison between transit and non-transit households provided in Table 4.2 are indicative of the trade-offs inherent to total time available, residential location, and trip-chaining behavior discussed in Chapter 3.

Urban Form Variables

Although BATS2000 does not include land-use variables, it provides exact geographical information about the location of each of the 15,064 households. GIS coordinates permit a precise allocation of each household residential unit within each Census Bureau geographical unit of reference using GIS techniques. By linking each households' residential unit *x* and *y* geographic coordinates to GIS Census block-group maps of the San Francisco Bay area, we merged a comprehensive set of land-use variables with the travel diary dataset.[9] We obtained

[9] Detailed GIS maps and other geographical data are available online at the MTC website <http://78. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.78.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.77. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.76. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited

other variables related to non-residential land use from the 2000 U.S. Census Bureau County Business Patterns (CBP) data file. Table 4.4 describes these variables and data sources.

We intend to use the last two variables of Table 4.4 as proxy measures of centrality (CBD distance) and polycentricity (distance from the nearest subcenter). As mentioned in Chapter 3, monocentric models only consider measures of the strength of the relationship between CBD employment (and other activities located at the CBD) and travel behavior

TABLE 4.4 Urban Form Variables

Variable	*Definition*	*Source*
Gross population density	Number of persons/Census block group area size (square miles)	U.S Census Bureau Summary File 3
Dwelling units	Number of owner occupied units	U.S Census Bureau Summary File 3
Dwelling density	Number of owner occupied units/ Census block group area size (square miles)	U.S Census Bureau Summary File 3
Number of retail establishments	Total number of retail establishments within a zip code	U.S Census County Business Patterns: 2000
Retail establishment density	Total number of retail establishments/zip code area	U.S Census County Business Patterns: 2000
Number of wholesale establishments	Total number of retail establishments within a zip code	U.S Census County Business Patterns: 2000
Wholesale establishment density	Total number of wholesale establishments/zip code area	U.S Census County Business Patterns: 2000
Distance from CBD	Distance from CBD	BATS2000-GIS derived
Distance from subcenter	Distance from the nearest subcenter	BATS2000-GIS derived

2008.76.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.75. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.74. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.73.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.73. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.72. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.72.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.71. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.71. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.70.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.69. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.68. MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008.67.MTC. *GIS Maps and Data*. Maps and Data 2008 [cited 2008. www.mtc.org>.

Through decades of decentralization, the urban landscape has taken a polycentric form, with a number of clustered employment centers affecting both employment and population distributions. The majority of these centers is subsidiary to an older CBD. Such centers are usually called subcenters or sub-regional centers (a more formal definition of subcenter is a set of contiguous tracts with significantly higher employment densities than surrounding areas). The transportation includes few studies of the influence of subcenters on travel behavior. One such study is Cervero and Wu [55], who have examined the influence of subcenters in the San Francisco Bay Area on commute distances to conclude that employment decentralization has lead to increased travel. Studies treating subcenters generally take subcenters as exogenously determined either by assumption or by an empirical determination that makes use of specific density thresholds. There are no established methods to determine the number of subcenters present in any urban area. Existing methods rely on rules of thumb based on knowledge about specific geographic areas [79], while others account for an endogenous determination based on their impact on agglomeration and employment [80].

To account for urban decentralization and its effect on transit use, we adopt the Census definition of cities and designated places to first identify subcenters and then produce a distance measure between a household residential unit and the nearest subcenter.[10] In addition to the above variables, we obtained a set of explanatory variables to control for household idiosyncratic preferences for location. The literature provides some insight on the choice of land-use variables as controls or instrumental variables [48, 81-83].

Using the Summary 3 Census Bureau file, we obtained the following variables at the block-group level:

1. Stock of housing built before 1945 (number of housing units)
2. Housing median value (dollars; owner-occupied units)
3. Housing median age (years; non-rent units)
4. Housing size (median number of rooms; owner-occupied units)
5. House median monthly cost (owner-occupied units)
6. Percent of household living below poverty line
7. Diversity index (0 = homogeneous; 1 = heterogeneous neighborhood)

[10] According to the U.S. Census, a city is a type of incorporated place. A census designated place is a statistical entity consisting of a densely settled concentration of population that is not within an incorporated place, but is locally defined by a name.

The first variable has been used before as an instrumental variable in multivariate regression studies that considered travel behavior as endogenous to urban form [48, 81-83], while the remaining ones are unique to this study. Additional controls for neighborhood characteristics have also been used elsewhere. For example, the proportion of block-group or census-tract population that is Black and the proportion Hispanic have been used as instruments by Boarnet and Sarmiento [82] and the percent of foreigners by Vance and Hedel [84].

In this study we use variables one through five to control for idiosyncratic preferences for housing characteristics not directly affecting travel behavior but directly affecting the residential choice decision at the household level. We use variables six and seven as controls for neighborhood characteristics. In particular, the percentage of households living below poverty levels (henceforth defined as poverty) serves as a proxy for crime, while the diversity index (henceforth called diversity) is used as a proxy for ethnic preferences (i.e., moving into a neighborhood with similar ethnic characteristics). The latter is an index of ethnic heterogeneity that varies from zero (only one race living in the neighborhood) to one (no race is prevalent), similar to Shannon's diversity index [85].[11] As discussed in further detail in Chapter 5, poverty and diversity serve a dual role as instrumental variables when we treat transit station proximity, *WD*, endogenous to the model.

Table 4.5 and Table 4.6 present relevant sample mean values split by households by mode choice. Transit households tend to live in highly populated areas characterized by higher than average poverty levels, as well as smaller and older housing units. We also generated one-way analysis of variance tables (not reported here) that include an interaction term between transit household and the transit station dummy variable. All variables exhibit a significant difference in means, indicating that housing price, housing age, room size, neighborhood diversity and poverty levels differ across households according to their location and mode choice. To gain additional insight on the trade-off between residential location and preference for transit, Table 4.7 and Table 4.8 report the same measures of Table 4.5 and Table 4.6, but differentiate between households living in proximity to a transit station. We measure proximity using a Euclidean half-mile buffer around a transit rail line in existence when the BATS2000 travel survey was being conducted.

Transit Supply Variables

We include the following measures of transit supply:

- Presence of a transit stop at workplace
- Supply of park-and-ride within a half-mile of transit stop

[11] The Shannon Index is a measurement used to compare diversity between habitat samples. The comparison is made by taking into account the proportion of individuals of a given species to the total number of individuals in the set.

- Presence of a transit-oriented development (TOD) stop within a half-mile of residential unit

TABLE 4.5 Urban Form Variables by Household Type

Transit Household	*Gross Population Density (persons/mile^2)*	*Dwelling density (dwellings/mile$^{2)}$*	*Retail Establishments Density (number/mile^2)*	*Wholesale Establishment Density (number/mile2)*
No	7,911	3,313	18.4	6.9
Yes	15,173	7,198	43.1	12.6
Overall	9,144	3,974	22.5	7.9

TABLE 4.6 Housing and Demographic Variables by Household Type

Transit Household	*House Median Value ($)*	*House Median Age (years)*	*Housing Stock (% built before 1949)*	*Housing Size (rooms)*	*Households Median Income*	*Households Below Poverty*	*Diversity Index*
No	399,819	34.18	0.20	5.97	74,189.52	0.06	0.57
Yes	399,374	41.77	0.36	5.92	67,140.84	0.08	0.62
Overall	399,591	35.47	0.23	5.92	72,994.44	0.06	0.58

The relevance of transit station proximity to the workplace is confirmed by the literature, as seen in Chapter 3. For example, using BATS2000, Cervero [54] showed that the presence of a station within one mile of a workplace (with good accessibility) strongly influences both residential choice decisions and transit use. The relationship gets stronger as distance to the station declines.

The presence of park-and-ride lots nearby transit stops also positively influences transit ridership by improving accessibility to those households located farther than the one-mile threshold. Furthermore, as highlighted by TCRP Report 95 [86], the presence of park-and-ride lots provides increases opportunities to trip chain from the residence to the transit station on the way to work . The relevance of park-and-ride lots is measured by a dichotomous variable indicating the presence of a park-and-ride lot within a half-mile of a transit stop. To produce these transit-supply explanatory variables, the same GIS maps created by MTC as part of their transit station proximity study were used [87] (a detailed discussion of the GIS methodology is provided in Appendix G of the MTC study).

Finally, to test the relevance of urban design policies on transit patronage, we introduce in the model a dichotomous variable qualifying a transit stop as having the characteristics of a TOD station. TOD stops are characterized by land development policies geared at facilitating transit use by improving transit station accessibility (by reducing physical barriers), and by promoting mixed land-use development (residential and commercial) in their immediate surroundings. For example Cervero [54] used BATS2000 and census land-use data to evaluate transit-oriented development (TOD) impacts on ridership and self-selection. In his analysis, he notes that between 1998 and 2002 about 13,500 apartment and condominium units were built within a half-mile of urban stations of southern California and the San Francisco Bay Area, often using land previously occupied by park-and-ride lots; this makes the dataset suitable to also test the impact of TOD on ridership. We relied on the California Department of Transportation Transit-Oriented Database to identify these stations [88].

Table 4.9 summarizes the full set of endogenous and exogenous explanatory variables.

TABLE 4.9 List of Variables for Model Estimation

Variable	*Definition*	*Use*
inc	Household income	Socio-demographic
sch	Number of children of school age (pre-k to middle)	Socio-demographic
veh	Number of vehicles	Socio-demographic
own	Tenure (1 = owner; 0= renter)	Socio-demographic
licensed	Number of persons with driving license	Socio-demographic
tswork	Presence of a transit stop within 0.5 mile of workplace (1=yes, 0=otherwise)	Transit supply
prkride	Presence of a park-and-ride within 0.5 mile of a transit stop (1=yes, 0=otherwise)	Transit supply
ts_tod	Transit stop characterized as transit-oriented development stop (1=yes, 0=otherwise)	Transit supply
cbd_dist	Residential unit distance from CBD	Urban form/land use
subc_dist	Residential unit distance from nearest subcenter (cities and designated places)	Urban form/land use
r_est	Number of retail establishments, zip code level	Urban form/land use mix
w_est	Number of wholesale establishments, zip code level	Urban form/land use mix
hprice	Median house price, block group level	Residential/neighborhood characteristics
hage	Median house age, block group level	Residential/neighborhood characteristics
room	Median number of rooms owner occupied unit, block group level	Residential/neighborhood characteristics
inc_blkgrp	Median household income, block group level	Residential/neighborhood characteristics
pov	Proportion of households living below poverty line, block group level	Residential/neighborhood characteristics
div	Diversity index (ranges from 0 if block group level is ethnically homogenous to 1 if heterogeneous)	Residential/neighborhood characteristics
act_dur	Mean non-work activity duration	Travel behavior
act_tt	Mean travel time to non-work activities	Travel behavior
TC	Trip chain; number of non-work trip stops on the job-residence commute	Trip chaining behavior
AS	Household activity space; standard distance ellipse area (mile^2)	Spatial extent of non-work activities
RL	Residential location (home-work distance)	Household residential location
WD	Walking distance from the residential unit to the nearest transit station	Transit station proximity
D	Gross population density (persons/mile^2)	Urban Form

Method of Analysis

Given the structural framework of Chapter 3, the empirical test of the proposed hypotheses requires the use of structural equation modeling (SEM). SEM is used to capture the causal influences of the exogenous variables on the endogenous variables and the causal influences of the endogenous variables upon one another. The use of SEM in transportation research is linked to the development of activity-based modeling in travel behavior research, which explicitly points out the causal mechanisms underlying individuals' location and travel decisions. In the transportation literature there exist several applications of SEM using cross-sectional data. For example, Pendyala [89] uses SEM to investigate the homogeneity of causal travel behavior across a population of interest; Fuji and Kitamura [90] and Golob [91] develop models of trip generation developing models of activity duration and trip generation. Additional examples of applications of SEM using cross-sectional datasets are discussed by Golob [92]. There also more recent studies of the causal relationships among travel behavior and urban form that

are effectively represented in a structural equation framework [93-97]. Available methods include maximum likelihood estimation (ML), generalized least squares (GLS), two-stage least squares (2SLS), three-stage least squares (3SLS), and asymptotically distribution-free estimation (ADF).

Model I Results

Using the set of variables summarized in Table 4.7, we specify the first model of Chapter 3 with exogenous residential location, *RL*, and density, *D*, as

$$TC = \alpha_0 + \alpha_1 AS + \alpha_2 RL + \alpha_3 WD + \alpha_4 veh + \alpha_5 act_{tt} + \alpha_6 act_{dur} + \alpha_7 sch + \alpha_8 subc_dist + \varepsilon_1 \quad (4.4)$$

$$AS = \beta_0 + \beta_1 TC + \beta_2 D + \beta_3 act_dur + \beta_4 inc + \beta_5 r_estd + \varepsilon_2 \quad (4.5)$$

$$TD = \gamma_0 + \gamma_1 TC + \gamma_2 AS + \gamma_3 WD + \gamma_4 RL + \gamma_5 tswork + \gamma_6 prkride + \gamma_7 ts_tod + \gamma_8 veh + \varepsilon_3 \quad (4.6)$$

Equation (4.4) describes trip-chaining behavior occurring on the commute trip to and from the work location. Trip chaining, jointly determined with the activity space, *AS*, is affected by vehicle availability (*veh*) and transit-station proximity, activity travel time and duration (*act_tt* and *act_dur*), and household structure (*sch*). Vehicle ownership and transit proximity, together with household characteristics (income and children), affect the capability of engaging in complex tours.

Equation (4.5) describes how the spatial extent of non-work activities responds to changes in urban form, being affected directly by density levels and retail establishment concentrations (*r_estd*). Drawing from the work of Anas (2007) on trip-chaining behavior and non-work travel, we assume that activity space is a result of utility maximizing behavior determining goods consumption and non-work travel. As income levels increase, so does the demand for (normal) goods and travel. We assume that individuals have preferences for heterogeneity in consumption (convexity of indifference curves indicates preference for balanced consumption bundles). As assumed by Anas (2007), individuals prefer to visit different locations, a behavior that positively affects the size of the activity space.

Equation (4.6) describes the demand for transit trips as brought about by the necessity to engage in non-work travel (directly affected by *AS* and *TC*) and by the relative distance of the residential unit to the work location, *RL*. We expect that transit supply directly affects transit ridership in terms of transit station accessibility both at origin and destination. We also wish to test the relevance of TOD policies in affecting ridership by including the dichotomous variable *ts_tod*, which measures the impact of a TOD station.

All three equations pass the rank condition for identification. Equation (4.4) is overidentified, and equation (4.5) and (4.6) are classified as just identified. The results of a three-stage least square regression (3SLS) are displayed in Table 4.10.

The results show that the joint determination of trip chaining and the spatial extent of non-work activities relate to transit patronage as hypothesized in Chapter 3. The presence of a transit stop at

workplace (*tswork*) positively affects transit demand, as well as the presence of a TOD transit stop in proximity of the residence unit (*ts_tod*). The size of the activity space reduces as density increases, which, in turn, positively affects the demand for transit. This assumption, as stated in Chapter 3, relates more compact urban environments to increased transit patronage. As locations where non-work activities are more clustered, the need to engage in long and complex journeys requiring modes other than transit decreases, resulting in increased transit usage. The converse is also true, suggesting that policy interventions related to directly affect the clustering of non-work activity locations, such as mixed-land use policies, are likely to significantly affect ridership levels. However, the relevance of this relationship is better appreciated in a context where residential location is also treated as a choice variable (i.e., endogenous).

To better appreciate the magnitude of these effects, Table 4.11 reports point elasticities of transit demand with respect to selected explanatory variables. For example, to obtain the elasticity of travel demand with respect to changes in density, we use

$$\varepsilon_{TD,D} = \frac{dTD}{dD} * \frac{D}{TD} \tag{4.8}$$

where dTD/dD is from equation (3.4) of Model I.

Table 4.11 shows that, for example, a 20-percent increase in gross population density, *D*, which is equal to about 1,830 persons per square mile, produces an approximate nine-percent increase in transit demand (linked trips at household level). Transit station proximity also plays a relevant role. A doubling of the average walking distance, *WD*, to the nearest transit station, or an increase from 0.3 miles to 0.6 miles, decreases transit demand by 14 percent; at about one mile, transit demand declines by 28 percent.

The presence of a transit station (*tswork*) within a half-mile of the workplace increases transit demand by 69 percent. Living in proximity to a TOD transit station (*ts-tod*) increases transit demand by about 28 percent. There seems to be a ridership bonus associated with proximity to a station characterized by accessibility features intended to promote transit use.

TABLE 4.10 3SLS Regression Results—Model I

Equation	*Coefficient*	*Std. Error*	*P*
Trip chaining, TC			
RL	0.0096	0.0040	0.0160
AS	0.0648	0.1658	0.6960
WD	-0.0570	0.0137	0.0000
veh	-0.0793	0.0308	0.0100
act_tt	0.0014	0.0004	0.0010
act_dur	-0.0022	0.0003	0.0000
subc_dist	0.0439	0.0068	0.0000
sch	0.0778	0.0144	0.0000
constant	1.2771	0.2611	0.0000
Activity space, AS			
TC	0.5863	0.0592	0.0000
D	-0.0974	0.0121	0.0000
act_dur	0.0001	0.0002	0.6880
inc	0.0299	0.0050	0.0000
r_estd	-0.0022	0.0003	0.0000
constant	1.7226	0.1351	0.0000
Transit demand, TD			
TC	0.6548	0.0732	0.0000
AS	-0.3002	0.0920	0.0010
WD	-0.0800	0.0124	0.0000
RL	0.0057	0.0021	0.0070
tswork	0.3848	0.0422	0.0000
prkride	-0.0737	0.0514	0.1510
ts_tod	0.2063	0.1097	0.0600
veh	-0.0456	0.0221	0.0390
constant	-0.1256	0.1014	0.2150

Note: N= 8,229; F_{TC}*=49.3;* F_{AS}*=73.6;* F_{TD}*=122.1*

TABLE 4.11 Elasticity Estimates—Model I

Elasticity	*RL*	*WD*	*D*	*subc_dist*	*r_estd*	*tswork**	*ts_tod**
TC	0.087	-0.007	-0.044	0.109	0.000	-	-
AS	0.100	-0.008	-0.066	0.125	0.000	-	-
TD	-0.157	-0.137	0.475	-0.388	0.001	0.687	0.279

** Indicates a proportional change*

The model reports a negative elasticity between residential location, (*RL*) and transit use. This is consistent with the assumption that households characterized by longer commutes engage in more complex trip chains, which positively affect the spatial extent of non-work activities. With exogenously fixed transit supply, as the activity space expands, transit demand declines.

The results also show that transit demand is sensitive to the presence of nearby subcenters (*subc_dist*), or, in general, to decentralization. The negative sign associated with the elasticities shows that increased polycentricity significantly affects transit demand adversely. The farther a household lives from a subcenter, the less it uses transit. A 50-percent increase in distance to a subcenter (from 2.9 to 4.3 miles) decreases transit demand by about 19.4 percent. This is so because households tend to rely more on other transport modes to carry out more complex trip chains. This result is consistent with the current literature on transit competitiveness and polycentric metropolitan regions. For example, in a study of transit services and decentralized centers, Casello [98] finds that transit improvements between and within activity centers (i.e., subcenters) are necessary to realize the greatest improvements in transit performance.

Next, we extend Model I to ascertain the extent to which the above relationships are affected by treating residential location as a choice variable.

Model II Results

As in the literature review, residential self-selection refers to individuals or households preferring certain residential locations due to idiosyncratic preferences for travel. In applied work, if residential self-selection is not accounted for, findings tend to overstate the importance of policies to increase transit use by mixed-used development.

To deal with this issue, Model II treats residential location as endogenous while retaining density as exogenous. Theoretical considerations inferred in the development of the behavioral model lead us to specify a model where individuals can locate anywhere within an urban area, choosing a utility-

maximizing *job-residence pair.* This process is carried out in conjunction with the optimal choice of both consumption and non-work travel. A household optimally located at a distance to work engages in trip-chaining to benefit from time-savings gained by combining errands to and from work. Time savings can either be allocated to a move farther out or to engage in additional non-work travel.

We specify Model II as

$$TC = \alpha_0 + \alpha_1 AS + \alpha_2 RL + \alpha_3 WD + \alpha_4 veh + \alpha_5 act_tt + \alpha_6 act_dur + \alpha_7 sch + \alpha_8 subc_dist + \varepsilon_1 \quad (4.9)$$

$$AS = \beta_0 + \beta_1 TC + \beta_2 D + \beta_3 act_dur + \beta_4 inc + \beta_5 r_estd + \varepsilon_2 \quad (4.10)$$

$$TD = \gamma_0 + \gamma_1 TC + \gamma_2 AS + \gamma_3 WD + \gamma_4 RL + \gamma_5 tswork + \gamma_6 prkride + \gamma_7 ts_tod + \gamma_8 veh + \varepsilon_3 \quad (4.11)$$

$$RL = \delta_0 + \delta_1 TC + \delta_2 TD + \delta_3 hprice + \delta_4 hage + \delta_5 rooms + \delta_6 div + \delta_7 pov + \delta_8 own + \varepsilon_4 \quad (4.12)$$

We consider housing characteristics (pricing, age, size) as relevant factors affecting residential location, as well as neighborhood characteristics (ethnicity, crime). In terms of exclusion restrictions, Equation (4.12) assumes that while residential location is affected by travel decisions (trip chaining and transit use), housing and neighborhood characteristics do not directly affect travel behavior at the disaggregate level. Other housing-characteristics variables, such as the stock of housing built before 1945, are not included in Equation (4.12) as they serve the same role of those just discussed (beside being highly correlated with pricing and size, thus potentially causing multicollinearity).

Equation (4.10) passes the rank condition for identification and is classified as just identified. Table 4.12 displays the results of the 3SLS regression.

TABLE 4.12 3SLS Regression Results—Model II

Equation	*Coefficient*	*Std. Err.*	*P*
Trip chaining, TC			
RL	0.0096	0.0118	0.4130
AS	0.0725	0.1980	0.7140
WD	-0.0573	0.0142	0.0000
veh	-0.0786	0.0316	0.0130
act_tt	0.0014	0.0005	0.0020
act_m	-0.0022	0.0003	0.0000
subc_dist	0.0435	0.0070	0.0000
sch	0.0778	0.0144	0.0000
constant	1.2604	0.2673	0.0000
Activity space, AS			
TC	0.2357	0.0538	0.0000
D	-0.0858	0.0107	0.0000
act_m	-0.0007	0.0002	0.0000
hhinc	0.0412	0.0045	0.0000
r_estd	-0.0014	0.0003	0.0000
constant	2.0943	0.1202	0.0000
Transit demand, TD			
TC	0.6964	0.0753	0.0000
AS	-0.2598	0.1157	0.0250
WD	-0.0669	0.0127	0.0000
RL	-0.0090	0.0088	0.3110
tswork	0.3716	0.0446	0.0000
prkride	-0.0669	0.0524	0.2020
ts_tod	0.1304	0.1147	0.2560
veh	-0.0365	0.0221	0.0990
constant	-0.1119	0.1020	0.2720
Residential location, RL			
TC	3.7324	0.5009	0.0000
TD	-1.2408	0.4660	0.0080
hprice	-2.8117	0.2722	0.0000
hage	-0.0849	0.0094	0.0000
rooms	1.1279	0.1468	0.0000
div	-2.6312	0.7238	0.0000
pov	-5.9629	2.4133	0.0130
own	0.4966	0.2658	0.0620
constant	39.1808	3.3743	0.0000

Note: N= 8,212; F_{TC}*=42.7;* F_{AS}*=72.5;* F_{TD}*=118.5;FRL=57.2*

The relevant signs and coefficient magnitudes of the first three equations are consistent with those of Model I. Table 4.12 reports a negative sign but statistically insignificant sign of the effect of residential location on transit demand (TD_{RL}). This might be due to the transit supply characteristics where the travel survey was conducted (e.g., fairly well-served commute routes). The parameter does not have a *ceteris paribus* interpretation as it changes concurrently with the other endogenous variables. Compared to Model I, changes in activity space negatively affect transit use. More dispersed activity-travel locations result in reduced transit patronage, although this effect is now less important.

As with Model I, we produce the relevant point elasticities, summarized by Table 4.13 (only reporting statistically significant estimates).

TABLE 4.13 Elasticity Estimates—Model II

Elasticity	*WD*	*D*	*subc_dist*	*r_estd*	*tswork**
TC	-0.009	-0.036	0.108	-0.014	-
AS	-0.003	-0.069	0.041	-0.232	-
TD	-0.028	0.269	0.065	0.170	0.766
RL	0.002	-0.027	0.052	-0.017	-

** Indicates a proportional change*

Compared to Model I, the endogenous treatment of residential location reduces the magnitude of the elasticity of travel demand with respect to density elasticity by 56 percent. When households can locate anywhere in an urban area and they adjust trip chaining and commuting costs, an exogenous 20-percent increase in density produces a 5.4-percent increase in the demand for transit (household linked trips). Transit station proximity to the workplace, however, increases in importance. The presence of a transit stop within a half-mile of the workplace increases transit demand by about 76 percent.

Accounting for self-selection reduces the relevance of transit-station proximity indicated by an 80-percent decrease in magnitude in its point elasticity estimate with respect to Model I. An increase from 0.3 to 0.6 miles to the nearest transit station reduces transit demand by only 2.8 percent as opposed to the 14 percent reduction of Model I. This result shows that self-selection is more relevant than what noted by Cervero (2007), who found that self-selection accounts for about 40 percent of transit ridership for individuals residing near a transit station.

To understand the reasons for these changes, it is sufficient to look at the specification of Model II. Equation (4.12) assumes households optimally choose residential location and non-work activities, which also optimally define the spatial extent of non-work activities. Households locate their residences farther from the job locations, trading lower housing costs against increased commute distance. Trip

chaining optimization is part of this trade-off process, which leads to an expansion of the activity space. This in turn reduces the opportunities to use transit to engage in non-work travel. This behavior is empirically validated by the statistical significance of all housing and neighborhood controls in equation (4.12).

Model III Results

Up to this point, we have treated urban form as exogenous. What happens if urban form, as measured by gross population density, is affected by travel decisions? To what extent is the relationship between density and transit in Model I and Model II affected by treating density as endogenous? The following model endogenizes density

$$TC = \alpha_0 + \alpha_1 AS + \alpha_2 RL + \alpha_3 WD + \alpha_4 veh + \alpha_5 act_tt + \alpha_6 act_dur + \alpha_7 sch + \alpha_8 subc_dist + \varepsilon_1 \quad (4.13)$$

$$AS = \beta_0 + \beta_1 TC + \beta_2 D + \beta_3 act_dur + \beta_4 inc + \beta_5 r_estd + \varepsilon_2 \quad (4.14)$$

$$TD = \gamma_0 + \gamma_1 TC + \gamma_2 AS + \gamma_3 WD + \gamma_4 RL + \gamma_5 tswork + \gamma_6 prkride + \gamma_7 ts_tod + \gamma_8 veh + \varepsilon_3 \quad (4.15)$$

$$RL = \delta_0 + \delta_1 TC + \delta_2 TD + \delta_3 hprice + \delta_4 hage + \delta_5 rooms + \delta_6 div + \delta_7 pov + \delta_8 own + \varepsilon_4 \quad (4.16)$$

$$D = \vartheta_0 + \vartheta_1 RL + \vartheta_2 AS + subc_dist + \vartheta_3 cbd_dist + \varepsilon_5 \quad (4.17)$$

Equation (4.17) treats as endogenous population density at the residential unit location. This model introduces exogenous variables serving as a proxies for centrality dependence (*cbd_dist*) and for polycentricity (*subc_dist*). Compared to Model I and Model II, the joint endogenous treatment of residential location and density produces a model whose relevant hypotheses are confirmed.

Regarding Equation (4.17) both CBD and subcenter distance are statistically significant. The sign of the CBD measure of centrality (*cbd_dist*) is negative as expected. As distance to the CBD or the nearest subcenter increases, density decreases. This finding indicates the spatial attraction of the CBD relative to subcenters even within a polycentric urban area, such as the San Francisco Bay area.

The relevance of these two variables is better highlighted by the elasticities presented in Table 4.15.

The elasticity of travel demand with respect to walking distance is less than that of Model I, but greater (in absolute terms) than that of Model II. An increase from 0.3 to 0.6 miles to the nearest transit station reduces transit demand by 9 percent, compared to the 14-percent reduction of Model I and 2.4-percent reduction of Model II. The presence of a transit stop at the workplace almost doubles the demand for transit, substantially increasing the importance of that variable in this model as compared to the others.

The sign and statistical significance associated with the centrality measure (*cbd_dist*) confirms the relevance of the CBD as a generator of transit ridership. Treating density endogenously results in a more elastic travel demand with respect to distance to the nearest transit center. It is relevant to note that both *cbd_dist* and *subc_dist*, appear as explanatory variables but are treated as endogenous in the model. An initial specification treated these two variables as exogenous, but overidentification tests (discussed in the next chapter) revealed that this treatment led to weak instruments (a problem leading to inconsistent estimates).

The exogenous treatment of subcenters assumes that they directly affect density, *D*, without being affected by its changes. The literature on the formation of subcenters demonstrates that the exogenous treatment of subcenters presents problems related to their identification and to the role they play in affecting both employment and population density. Recent studies show that the formation of subcenters is endogenous to the process leading to urban development (i.e., subcenters are endogenous to changes in density) [80]. Thus this study treats them as endogenous.

TABLE 4.14 3SLS Regression Results—Model III

Equation	*Coefficient*	*Std.Error*	*P*
Trip chaining, TC			
RL	0.0777	0.0158	0.0000
AS	1.0087	0.2241	0.0000
WD	-0.6626	0.0554	0.0000
veh	-0.0292	0.0316	0.3570
act_tt	-0.0009	0.0005	0.0560
act_m	-0.0004	0.0003	0.2650
subc_dist	0.1875	0.0317	0.0000
sch	0.0570	0.0132	0.0000
constant	-2.9369	0.3204	0.0000
Activity space, AS			
TC	0.5389	0.0654	0.0000
D	-0.2817	0.0002	0.0000
act_m	0.0000	0.0050	0.8390
hhinc	0.0182	0.0316	0.0000
r_estd	-0.0018	0.0010	0.0000
constant	3.5109	0.2583	0.0790
Transit demand, TD			
TC	0.2310	0.0782	0.0030
AS	0.2130	0.1103	0.0540
WD	-0.4740	0.0405	0.0000
RL	0.0162	0.0089	0.0700
tswork	0.4463	0.0414	0.0000
prkride	-0.0788	0.0457	0.0840
ts_tod	0.1280	0.0995	0.1980
veh	-0.0641	0.0204	0.0020
constant	-1.3114	0.1379	0.0000
Residential location, RL			
TC	2.4695	0.4889	0.0000
TD	1.1677	0.4700	0.0130
hprice	-2.7930	0.2491	0.0000
hage	-0.0961	0.0080	0.0000
rooms	1.3432	0.1071	0.0000
div	-6.1904	0.5571	0.0000
pov	-4.5075	1.6515	0.0060
own	1.3780	0.1901	0.0000
constant	40.3105	3.0969	0.0000
Density, D			
RL	-0.0091	0.0108	0.4000
AS	-0.5333	0.0710	0.0000
cbd_dist	-0.0401	0.0016	0.0000
subc_dist	-0.0707	0.0301	0.0190
constant	11.7688	0.1800	0.0000

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

TABLE 4.15 Elasticity Estimates—Model III

Elasticity	*WD*	*subc_dist*	*cbd_dist*	*r_estd*	*tswork**
TC	-0.067	-0.195	-1.066	0.014	--
AS	-0.060	-0.088	-0.102	-0.009	--
TD	-0.093	-0.522	-1.177	-0.366	0.961
RL	-0.023	-0.076	-0.301	0.011	--
D	-0.012	-0.153	-2.972	-0.002	--

** Indicates a proportional change*

The elasticity of transit demand with respect to distance to the CBD (– 1.17) is greater in absolute value than the elasticity with respect to distance to the nearest subcenter (– 0.52). In other words transit patronage is more responsive to a residential location near the CBD than near subcenters. This is probably due to differences in existing transit station locations near the CBD compared to suburban areas. This result is inconsistent with recent findings that found increased transit use in better served decentralized urban areas [99, 100] and empirical findings showing that transit ridership is not affected by the CBD [101].

Next, we subject the models to post-estimation testing to confirm their statistical validity. We also discuss additional factors that could potentially affect the validity of results.

Post Estimation Tests

The models presented above explicitly deal with endogeneity of urban form and travel by applying simultaneous equation modeling. As seen, the first step requires correctly identifying a model. This step generates models that are either just identified or overidentified, based on the number of exclusion restrictions applied to each equation (See Appendix B for more details).

Tests of Endogeneity and Overidentification

A property of the 3SLS regression is its loss of efficiency if the explanatory variables treated as endogenous are, in fact, exogenous, making its use unnecessary when compared to OLS. It is thus useful to test the explanatory variables suspected to be endogenous to the model.

The null hypothesis of the endogeneity test is that an OLS estimator of the same equation would yield consistent estimates; that is, any endogeneity among the regressors would not have deleterious effects on the OLS estimates. A rejection of the null hypothesis indicates that endogenous regressors' effects on the estimates are meaningful, and instrumental variables are required. The test was first proposed

by Durbin [102] and later by Wu [103] and Hausman [104]. The procedure to test endogeneity of multiple explanatory variables requires (i) estimating in reduced form each endogenous variable on all exogenous variables (including those in the structural equation and those used as instruments; i.e., the explanatory variable included in the other equations); (ii) adding the estimated error terms back into the structural equation; and, (iii) testing for the joint significance of these residuals in the structural equation. Joint significance indicates that at least one variable is endogenous to the model. Under the null hypothesis, the test statistic is distributed χ_q^2 (Chi-squared) with q degrees of freedom, where q is the number of regressors specified as endogenous in the original instrumental variables regression. The procedures to conduct this test are available in Stata® (the statistical package used in this study) using the *ivreg2* routine (specifically, by using the command *ivendog*) developed by Baum et al. [105].

Furthermore, after verifying the presence of endogeneity, additional tests are needed to confirm the correct choice of the exclusion restrictions characterizing the system of equation. These tests are needed to confirm the proper choice of instruments and to eliminate doubts of a poor model performance (bias and inconsistency). The overidentification tests used here are conducted by regressing the residuals from a 3SLS regression on all exogenous variables (both included exogenous regressors and excluded instruments). Under the null hypothesis that all instruments are uncorrelated with the residuals, a Lagrangean multiplier (LM) statistic of the form NxR^2 (N = number of regressors, while R^2 is calculated from the residuals' regression), has a large sample Chi-squared distribution, χ_r^2, where r is the number of *overidentifying* restrictions (i.e., the number of excess instruments). If the hypothesis is rejected, there is doubt about the validity of the instrument set; one or more of the instruments do not appear to be correlated with the disturbance process. The Stata® procedure reports the Sargan [106] overidentification test (using the *overid* command).

Finally, when dealing with a relatively large number of exclusion restrictions, a situation encountered in Model III, it has been shown that the power of the overidentification tests is reduced [105]. Furthermore, there is a need to be able to test subsets of instruments to identify weak ones, which would adversely affect validity of results. In this context, another test statistic can be used to test a subset of instruments; the *difference-in-Sargan* test, or *C* test. The statistic is computed as the difference between two statistics; one obtained by regression using the entire set of instruments and a second one obtained with the smaller set of restrictions (excluding the suspected variables). Under the null hypothesis that the variables are proper instruments, the *C*-test statistics is distributed $\chi_k^2$with k degrees of freedom equal to the number of suspect instruments being tested.

Table 4.17 reports the results of the endogeneity and overidentification tests for the travel demand equation, *TD* (the same tests and same results were obtained for the other equations but are not reported here). The Durbin-Wu-Hausman (DWH) test is numerically equivalent to the standard Hausman endogeneity test. Results across the three models indicate the presence of endogeneity, confirming the appropriateness of 3SLS versus OLS regression.

Model III fails the overidentification test in its initial specification that treated the land-use measures (*cbd_dist*, *subc_dist*, *r_estd*) as exogenous to the system (Sargan test = 24.951; *p-value* = 0.0030). After

their endogenous treatment, Model III passes the overidentification test, as signaled both by the Sargan (7.1540 with *p-value* of 0.3068) and *C* tests.

Overall, the tests indicate that SEM is an appropriate technique and that the equation specifications of Chapter 4 produce models that also pass the overidentification tests. The validity of the models allows making conclusions regarding the parameters of interest.

Other Issues

TABLE 4.17 Endogeneity and Overidentification Tests

Test	*Model I*	*Model II*	*Model III*
Wu-Hausman *F* test	78.073	83.369	13.000
p-value	0.000	0.000	0.000
Durbin-Wu-Hausman χ^2 test	153.423	243.059	90.217
χ^2 p-value	0.000	0.000	0.000
Anderson canon. corr. LR statistic (identification/IV relevance test):	42.137	27.137	33.524
χ^2 p-value	0.000	0.003	0.000
Sargan statistic (overidentification test of all instruments):	9.638	11.365	24.951
χ^2 p-value	0.057	0.252	0.003
Sargan statistic without suspect instruments*	-	-	7.154
χ^2 p-value	-	-	0.307
C statistic (exogeneity/orthogonality of suspect instruments)**			17.798
χ^2 p-value			0.001

** Test conducted after endogenous treatment of: cbd_dist, subc_dist, r_estd*

*** Test conducted on exclusion of instruments: cbd_dist, subc_dist, r_estd*

Summary of Findings

This study sought to overcome shortcomings of the empirical literature modeling of the relationship between transit travel behavior and urban form. A review of the current state of empirical research on the subject uncovered the main weaknesses of findings relating the built environment to travel behavior as well as noting the paradigm shift epitomized by the activity-based literature. The findings of this review show that there has been a shift from the study of density threshold levels that make transit cost-feasible to an analysis of the effect of urban design and land-use mix on travel behavior, after controlling for density levels. The issue is no longer at what density thresholds it makes sense to implement transit, but what is the best set of policies affecting urban design and land-use mix that most influences the spatial arrangements of activity locations, so that individuals are more likely to utilize transit. This shift is reflected by an increasing number of studies that assess the relevance of transit-oriented development (TOD) to transit use when households or individuals prefer certain urban setting to others.

While early work sought to provide a framework that made use of aggregate data, the more recent literature models the simultaneous decision of location and travel when individuals choose locations based on idiosyncratic travel preferences.

Finally, there is a lack of empirical work that examines the relationship between urban form and travel behavior within an analytical framework that takes into account the complexity of travel by considering trip chaining among other travel complexities. To avoid these shortcomings and to incorporate the activity-based approach, we developed and estimated a simultaneous equation model of transit usage and urban form.

The models presented here are innovative in many aspects, above all for its explicit incorporation of the links between consumption, travel, the spatial location of non-work activities, and the ensuing interrelationship with the surrounding built environment.

The empirical application of the behavioral model requires the use of simultaneous equation modeling. The biggest challenge when employing structural equation modeling lies in defining properly specified models. The necessary identification leading to the rank condition are paramount to reliable estimates. The literature reviewed in this study revealed that none of the papers and studies formally follows this process.

Empirically Estimable Model of Transit and Urban Form

The models of presented here allow household travel to respond to changes in urban form, by considering trip-chaining for non-work travel. In the model, trip-chaining results from households' reductions in non-work travel time while accounting for constraints that the built environment imposes. Any travel-time saving is spent on additional non-work travel or provides inducement to reassess residential location decisions. These changes in travel behavior and residential location then affect the demand for travel.

The constraints imposed by the built environment are captured by the activity space. Empirical evidence in Chapter 4 shows that lower densities define a larger activity space, which, in turn, decreases transit use. Conversely, as density increases, the activity space contracts, as does the need to engage in complex trip chains. Idiosyncratic preferences for transit also affect transit demand. For example, in the absence of adequate transit, households that need to engage in complex trip-chain patterns, independent of changes in the surrounding built-environment, may use the automobile. In contrast, if adequate transit services are available to accommodate their travel patterns, households would choose transit, other things equal.

To facilitate a summary of Chapter 4's findings and for ease of comparison, Table 5.1 presents elasticities from the three estimated models (only statistically significant results are shown).

Exogenous density change does not have a large effect on transit demand, and the magnitude of the effect decreases when residential location becomes endogenous. A 20-percent increase in gross population density (1,830 persons per square mile) increases transit demand from a minimum of 5.4 percent to a maximum of 9.5 percent.

TABLE 5.1 Relevant Land-Use and Transit-Supply Elasticities of Transit Demand

Elasticity	*Model I*[a]	*Model II*[b]	*Model III*[c]
Density	0.475	0.269	n/a
Walking distance	-0.137	-0.028	-0.093
*Transit station at workplace**	0.687	0.766	0.961
*TOD station**	0.279	n/a	n/a
Distance to CBD	n/a	n/a	-1.177
Distance to nearest subcenter	-0.388	-0.065	-0.522
Retail establishments density	0.001	0.170	n/a
Residential location	-0.157	n/a	n/a

[a] residential location exogenous; density exogenous

[b] residential location endogenous; density exogenous

[c] residential location and density endogenous

n/a = not available

* Indicates a proportional change

The importance to transit demand of station proximity, as measured by walking distance, decreases after accounting for idiosyncratic preferences for location. In Model III, the elasticity of transit demand with respect to walking distance is about one-third smaller than in Model I, in which residential location and density are exogenous. This decline in magnitude is due to allowing households to choose their residential location and by accounting for omitted-variable bias error. This contrasts with what found by Cervero [54], who shows that self-selection accounts for about 40 percent of transit ridership for individuals residing near a transit station.

The presence of a transit station in proximity to a workplace also has a significant positive impact on ridership, as indicated by the magnitude of the proportional changes across all three models.

In Model I, transit-oriented development near transit stations has a positive impact on transit use; a TOD stop increases transit demand by about 28 percent. In conformity to the literature, a transit station near a workplace exerts a positive impact on ridership, as indicated by the magnitude of the proportional changes across all three models.

An established central business district (CBD) is still a relevant driver of transit use, as highlighted by an elasticity of transit demand with respect to distance to the CBD of –1.17. Although subcenters play a less important role, our findings support a policy of providing transit services in decentralized employment and residential areas to increase ridership. The importance of mixed-use development to increase transit patronage is highlighted by the elasticity of travel demand with respect to retail establishment density. Model II shows that a 20-percent increase in retail establishment density (or about 28 establishments per square mile) increases transit demand by 3.4 percent.

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

The major contribution of this research effort is the development of a simultaneous equation model of transit patronage and land-use that acknowledges the interrelationship between travel behavior and urban form.

Another contribution of this dissertation is the empirical treatment of density as an explanatory variable for trip-making behavior. As opposed to the current practice of regressing trip making behavior against density measures, we assume that density does not directly to affect the demand for travel. In our models, density first directly affects the spatial dispersion of goods and services, as measured by the activity space. It is only by affecting the size of the activity space that density affects both trip chaining and the demand for transit services. The consequences introduced by this structure are not trivial and as demonstrated by the empirical results.

Notwithstanding the validity of the post-estimation tests, there still exists the possibility that some of the variables treated as exogenous are, in fact, endogenous. For example, this study treats vehicle ownership as exogenous. The literature review, however, revealed studies that consider vehicle ownership endogenous to residential location and density. One extension to this research, therefore, would be to include an endogenous treatment of this and other mode-choice variables.

Another extension would be to include leisure time available to households. Indeed, the behavioral model presented here assumes that households can save time by engaging in trip chaining. Time savings are then reallocated to either more non-work travel or to an extended commute. The model does not explicitly explain what happens to leisure time. The inclusion of total time constraints that includes all relevant time uses (in-home and out-of-home) would provide insight on time use and its effect on trip chaining.

Finally, in contrast to multiple linear regression analysis, nonparametric estimation methods would permit less restrictive assumptions. These methods can uncover the presence of nonlinearities among dependent and independent variables which could lead to a better parameterization of equations of interest. Although nonlinearity in trip-chaining formation and density levels is better captured by these methods than by more commonly used techniques, being computationally challenging, they are rarely used in applied work, especially in the field of travel behavior research and simultaneous equation modeling. Further research that makes use of these methods is warranted.

A4. Data Sources

- **Freeway Speed (2009):** Exhibit A-8, Schrank, D., Lomax, T., and Turner, S., Urban Mobility Report 2010, Texas Transportation Institute, December 2010

  http://www.inrix.com/urbanmobilityreport.asp

- **Arterial Speed (2009):** Exhibit A-8, Schrank, D., Lomax, T., and Turner, S., Urban Mobility Report 2010, Texas Transportation Institute, December 2010

  http://www.inrix.com/urbanmobilityreport.asp

- **Household Income (2007-2009):** Table B19013 Median household income in the past 12 months (in 2009 inflation-adjusted dollars), 2007-2009 American Community Survey 3-Year Estimates
  http://factfinder.census.gov/servlet/CTTable?_lang=en&_ts=338382979366

- **Population Density:** G001 Geographic Identifiers, 2010 Demographic Profile Data**,** US Census Bureau
  http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DEC_10_NSRD_GCTPL2.US41PR&prodType=table

- **Housing Data:** G001 Geographic Identifiers, 2010 Demographic Profile Data, US Census Bureau
  http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DEC_10_NSRD_GCTPL2.US41PR&prodType=table

- **Mode Share (Auto, Ride, Van, Transit, Walk, etc):** Table B08301, Means of transportation to work Universe: Workers 16 Years and over, 2007-2009 American Community Survey 3 – Year Estimates
  http://factfinder.census.gov/servlet/CTTable?_lang=en&_ts=338384608377

- **Occupation (Agriculture, Construction, Transportation, etc):** Table B24050, Industry by Occupation for the Civilian Employed Population 16 years and over Universe: Civilian Employed Population 16 years and over, 2007-2009 American Community Survey 3 – Year Estimates
  http://factfinder.census.gov/servlet/CTTable?_lang=en&_ts=338385094009

- **Geographic Area:** G001 Geographic Identifiers, 2010 Demographic Profile Data**,** US Census Bureau
  http://factfinder2.census.gov/faces/tableservices/jsf/pages/productview.xhtml?pid=DEC_10_DP_G001&prodType=table

- **Retail Establishments:** 2009 MSA Business Patterns (NAICS), US Census Bureau http://censtats.census.gov/cgi-bin/msanaic/msasect.pl

- **Vehicle per Household:** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18443.html

- **Average Vehicle Occupancy:** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18444.html

- **Annual Transit Trips:** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18447.html

- **Per Capita Personal Income:** 2009, Bureau of Economic Analysis, US Department of Commerce http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=3

- **Home to Work Distance:** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18450.html

- **Average Trip Length (Car, Van, Motorcycle, etc):** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18445.html

- **Walking Distance to Public Transit:** U.S. Department of Transportation, Federal Highway Administration, 2009 National Household Travel Survey. http://nhts.ornl.gov/tables09/ae/work/Job18451.html

- **Hourly Wages:** May 2010 Metropolitan and Nonmetropolitan Area Occupational Employment and Wage Estimates, Bureau of Labor Statistics, US Department of Labor http://www.bls.gov/oes/current/oessrcma.htm