

ABSTRACT

DAVIS, ALISON FARA. The Impact of Traffic Congestion on Household Behavior: Three Essays on the Role of Heterogeneity. (Under the direction of V. Kerry Smith).

Congestion is increasing everywhere from established urban areas to growth centers. The rate of increase is greater in these rapidly growing areas of the country. With the explosion of congestion in rapidly growing areas, how does congestion influence individual decision making? The purpose of this thesis is to investigate how congestion affects people's choices. More specifically, this research considers the role of observable household attributes as conditioning factors, influencing behavioral responses to congestion. This analysis is developed through three separate essays.

The first essay focuses on commuting time as the outcome of joint residential and employment decisions. The framework hypothesizes that information about individual preferences for avoiding commuting time can be revealed through the differences in spatial distributions of commuting time. Two different choice margins are selected for the next two essays: a long term margin which would be associated with residential location decisions; and short term choice margins within the context of a random utility model for non-working trips. The second essay hypothesizes that expected congestion is sufficiently important to be displayed in one of a household's most important decisions, the selection of residential location. The effect of congestion can be captured with a hedonic price framework assuming that households select residential locations based on an expected mix of trips. The focus of the third essay changes to individual trips. That is, it hypothesizes household constraints will influence an individual's sensitivity to congestion as displayed through the members' decisions to make individual trips. This

process is modeled using a random utility framework with careful attention to the transformation of a trip into a choice.

This research provides evidence that household characteristics influence both long and short term decisions. There is support for the hypothesis that there are some household circumstances that limit the members' abilities to respond to congestion. The multiple time constraints on the activities that need to be undertaken, and the discretion in when they can be undertaken in relation to other commitments, limit each individual's ability to adapt to congestion. Furthermore, this study recognizes that household circumstances are also important factors driving the distribution of commuting times.

The Impact of Traffic Congestion on Household Behavior:
Three Essays on the Role of Heterogeneity

By

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Biography

Alison Davis was born in 1975 to Amy and Dudley Davis in Baltimore, MD. She graduated from Pikesville High school in 1993. After graduating from Skidmore College with a Bachelor's degree in economics, she spent the next three years in the food service industry. Alison entered N.C. State University in 1999 to begin the PhD program in economics. Upon the receipt of her PhD, she will begin her career at the University of Nevada as a research assistant professor.

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Chapter One

1.1. An Introduction to Household Travel Behavior

Congestion is increasing everywhere from established urban areas to growth centers. The rate of increase is greater in these rapidly growing areas of the country. The percentage of travel completed during congested conditions increased by 200% in medium-sized urban areas compared to 72% in the largest urban areas between 1982 and 2001.¹ 85% of the roads for these medium sized urban areas were not congested in 1982, but in 2001 only 11% of the roads remained free of congestion. As expected, commuting times have also increased. Over a five year period, commuting times for households have increased from 2% to 11% depending on the size of the city.² With the explosion of congestion in rapidly growing areas, how does congestion influence individual decision making? The purpose of this thesis is to investigate how congestion affects people's choices. More specifically, this research considers the role of observable household attributes as conditioning factors, influencing behavioral responses to congestion. This analysis is developed through three separate essays.

Activities, whether they involve work, leisure, or consumption, all require individuals use time. The time is not exclusively associated with the consumption, work, or the leisure. There is also the time required to initiate or complete the activity that may be different from the time spent participating in the specific event. This additional time

¹ As reported in the Urban Mobility Report in 2001. A medium sized area is defined to have a population between 250,000 and 500,000 households. An extra large urban area is defined to have a population of more than 3 million households.

² This statistic was calculated using responses from the 1990 and 1995 National Personal Transportation Surveys.

may be considered a transactions cost that is implicitly a part of the “full” price of most activities. Regardless, all individuals must transport themselves to the locations of activities they choose to engage in. Traffic congestion influences the nature of these time requirements. Therefore, it increases the costs of undertaking every activity.

Constraints imposed by each household’s circumstances limit its members’ ability to respond to congestion. For example, an individual with a fully flexible work schedule can avoid congestion by spreading trip taking over non-congested periods. More households have both members working, substituting purchased services for what was once produced in the home. Moreover, the nature of work within the home and its allocation among household members has changed over the past three decades, creating additional time constraints. Time usage outside the household has also changed. Households with multiple earners and children face complex co-ordination and scheduling tasks that may well make it difficult for them to alter the timing of trips and avoid congestion.

There are several ways to evaluate the importance of household circumstances as an influence of an individual’s sensitivity to congestion. The most natural way would be to consider how commuting times are influenced by household structure. Households tend to sort themselves into neighborhoods based on their preferences for housing attributes together with the demands imposed from the locations for work. The selection of a neighborhood in relation to the workplace seems likely to balance a number of considerations – work trips for working members as well as other demands that will vary with composition of each household. Once a decision is made to select a neighborhood it will imply, given the spatial structure of the area, a distribution of commuting times

under ideal conditions. The urban structure is defined by the areas of available housing, the locations of employment centers, and the road infrastructure.

The first essay focuses on commuting time as the outcome of joint residential and employment decisions. The framework hypothesizes that information about individual preferences for avoiding commuting time can be revealed through the differences in spatial distributions of commuting time. This analysis observes outcomes of households' responses to congestion at the census block group level. The hypothesis is that household heterogeneity, as measured by attributes at the census block group, will influence the observed distributions for commuting times. For example, factors such as household composition, income, and other socio-economic factors are expected to be important determinants of mean commuting time and other moments of the commuting time distribution.

Two different choice margins are selected for the next two essays: a long term margin which would be associated with residential location decisions; and very short term choice margins within the context of a random utility model for non-working trips. For both of these cases, it is hypothesized that measures of congestion affect choices and thus are important to individuals making those choices. In addition, observable attributes of the household are thought to distinguish the ways in which the models test for how people can respond to congestion.

The second essay hypothesizes that expected congestion is sufficiently important to be displayed in one of a household's most important decisions, the selection of residential location. The model follows from a slight modification of Becker's (1965) household production function. When choosing a home, a household has an expectation

about the number and type of trips that they will need to complete on a regular basis. The mix of trips a household expects to make is conditional on the structure of the household (i.e. the number and age of children, dual earner vs. single earner, etc.). If congestion influences the time required to complete these activities then it is expected that it will also be a factor in residential location decisions. These outcomes can be captured with a hedonic price framework. However, the analysis recognizes that congestion is induced by households' locational choices. Thus it should, in principle, be determined along with the price as part of the equilibrium. As a result, congestion should be treated as an endogenous variable. In addition, if the location of a house influences its price, then the possibility arises that nearby houses will be affected by the same location factors. Any error in measuring these neighborhood effects will cause their error terms to be correlated. Thus, the estimator should also address the potential for spatial autocorrelation.

The focus of the third essay changes to individual trips. That is, it hypothesizes household constraints will influence an individual's sensitivity to congestion as displayed through the members' decisions to make individual trips. This process is modeled using a random utility framework with careful attention to the transformation of a trip into a choice. By evaluating how several different dimensions of a trip are translated into the specification of choice alternatives, it is possible to test how household attributes influence the individual's response to congestion. In the process, the definition of the choice set affects this role. Past literature has focused the analysis of congestion on trips made for work purposes. Therefore, this methodology addresses the more interesting question and incorporates trips made for non-work purposes.

Each of the essays requires the imputation of a congestion measure that best captures what is hypothesized to be the congested conditions households face when making both long and short term choices. The first essay investigates the influences of household characteristics on commuting time. The distribution of commuting times as reported by households within a census block group is the measure of congestion used in this essay. It is expected that reported commuting time reflects both distance (sprawl) and congestion. The ideal measure would involve the differential between the reported commuting time and a baseline measure of commuting time, travel time in the absence of congestion. However, that measure is not currently available. Thus, we use reported commuting time, but assume that this measure includes some error. Because commuting time is the dependent variable in this instance, we do not need to worry about endogeneity issues.

In the second essay, we explore the effect of two different measures of congestion on housing prices. It is expected that these variables are reflecting different types of congestion. Reported commuting time is again introduced as a measure of congestion with the same understanding that it includes some error. However, now the congestion variable is an independent variable. Thus, it is expected to be endogenous. In addition, congestion is also defined as a physical measure by using the density of cars on a road structure, controlling for capacity. This measure is localized around the residential location by attaching the closest traffic count station, where the densities are recorded, to a residential location. In most instances, the closest traffic count station is less than one mile away from the home. Thus, the measure likely provides an adequate description of road conditions near the residence. While the commuting time variable limits the impact

of congestion to the work trip, this physical measure of congestion is thought to be a proxy for congestion that would be faced while making all types of trips. As in the first essay, this is not necessarily the ideal measure. Instead, congestion measured along the entire route of a trip would be optimal. Because trips are unobserved in this essay, those data are not available.

Finally, in the third essay, we look at how household circumstances influence the impact of congestion on individual non-work trip choices. The optimal measure of congestion in this instance would be the required travel time to complete all of the specified activities during each time period of the day. However, the data offer this information as an ex post outcome only for the choice that was taken. Thus, we must create a proxy for what individuals are likely to consider as factors in the travel time for each of the choice alternatives. Two variables are introduced. A vehicle count that varies by time of day and a distance measure that varies by activity location. Vehicle counts are collected at traffic count stations throughout the county. In addition, time varying vehicle counts are collected at a selection of busy intersections. The closest traffic count station and intersection is attached to each residential location, providing a measure of time-varying congestion for each household. The distance measure does not necessarily reflect the true distance to each activity. Because the data do not provide information on the exact destination for each trip, vehicle miles traveled can not be calculated. Instead, we use the average distance from the residential location to the closest locations of each activity choice. The translation of the trip into a choice alternative will determine which of the two measures to include or perhaps both measures in some instances.

1.2. Motivation

Over the last thirty years, the nature of household labor force participation patterns has dramatically changed. The dual earner household is the predominant household type in households with more than two members over the age of sixteen.³ In the past, one member of the household, typically the father, would work and the mother would stay home and complete all of the household activities and care for the children. While in many instances there was a market service or product that could be purchased as a substitute for the woman's labor at home, it was rarely purchased. Moreover, it was deemed inappropriate for children to be brought up by anyone but their mother. Today, attitudes towards child rearing are different. The household takes into consideration both budgetary considerations and preferences for work. The explanation of the booming dual earner household is not limited to simply financial considerations, but also individual considerations, i.e. the desire to work.

The impact of women entering the workforce on the level of non-market household production was investigated by Langefeld and McCulla (2000). They estimated the monetary impact of household non-market production on GDP. Their analysis spanned from 1946 to 1997. The authors found that while market production grew faster as women entered the work force, home-based production grew at a slower rate. Specifically, the inclusion of household non-market services increased GDP by 43% in 1946 but by only 23% in 1997. These findings provide some evidence that the

³ U.S. Census 2000

trend in dual earner households has prompted households to purchase market services as opposed to producing them in the home in response to increasing time pressures.

The purpose of this section is to describe how time allocation has changed within the household over time and the influences of household composition on travel time. As a result of this trend, there are increasing time demands on dual earner households. These time constraints, as defined by specific household circumstances, dictate the ability of the household to respond to congested roadways. The first part of this section is devoted to describing time usage at a general level for men and women and what these transformations imply for both the constraints and the needs facing each household. This information is collected and analyzed from various national time use studies and transportation surveys.

The total amount of daily time that a household has to allocate to complete work, household work, and leisure is fixed. Therefore, any activity that requires more time than was previously allocated to it causes households to either redistribute their time or purchase someone else's. If the second member of the household decides to work a forty hour week, then that time must be sacrificed from other activities. Responses from two time-use studies are used to determine how the allocation of time has changed for both men and women. The first study collected time-use information from households from 1965-1985. The data were a compilation of three different studies collected in 1965, 1975 and 1985 from the Survey Research Centers from both the University of Michigan and the University of Maryland. A total of 7,345 cases were considered for this combined database. The second study is a comprehensive survey of 1,775 respondents aged 18 to 64 in the form of twenty-four hour recall time diaries completed by the

University of Maryland's Survey Research Center. The first half of the survey was done in 1998-99 and the second half with a parallel but separate national 2000-2001 diary sample.

Table 1.1 illustrates how individuals in a dual member household use their daily time, distinguished by sex. There was approximately a 40% increase in female weekly hours worked between the two studies. In addition, there was a 20% increase for male work hours per week. Because of this redistribution of time to work, time spent on other daily activity must be forgone. For example, it appears that over the two studies the male has assumed more responsibility for housework than in 1965-1985 but sacrifices time spent for amusement purposes, both in the home and out of the home, and he also sleeps less. The female completes just a bit less housework but is forced to give up amusements and sleep as well.

Travel is the only other activity that has required more time over time. The average woman traveled only about 8.77 hours per week and the average man traveled 10.88 hours per week in the first study. In the second study, women are traveling 10.76 hours per week (a 22.7% increase) and men are traveling 12.11 hours per week (an 11.3% increase). Before the surge of professional women in the workplace, the woman usually worked close to home and therefore her commute was typically short. Now women work in more specialized professions where the location of employment centers is less uniformly distributed around the residence, potentially implying a longer commute. In addition, because of time pressures, more household activities are being purchased out of the home, requiring either worker in the household to travel to pick someone up, get the dry cleaning, go shopping, etc. An alternative explanation for the

increase in travel time extending beyond increases in vehicle miles driven is that traffic congestion has increased the time required for travel.

Table 1.1 An individual's allocation of weekly time

	1965 – 1985 study⁴		1998 – 2001 study⁵		% Change	
	<i>Male</i>	<i>Female</i>	<i>Male</i>	<i>Female</i>	<i>Male</i>	<i>Female</i>
Work	41.31	32.4	49.85	44.9	20.7%	38.6%
Housework	7.73	17.88	12.29	16.75	59%	-6.3%
Personal Maintenance (sleep, eat, dress, bathe)	70.94	72.69	64.24	67.75	-4.5%	-6.8%
Amusement out of home (movies, sports, culture, visiting)	9.87	11.03	8.10	8.895	-17.9%	-19.4%
Amusement in home (relaxing, TV, radio, internet)	23.11	22.53	18.04	16.54	-21.9%	-26.6%
Religious/Civic/other organizations	1.42	1.38	1.46	1.34	2.8%	-2.9%
Exercise/Play Sports	2.95	1.72	1.94	1.05	-34.2%	-39%
Travel (work and non-work)	10.88	8.77	12.11	10.76	11.3%	22.7%

It is expected that various factors influence the household's travel time. For instance, gender is thought to play a small role. Women are still making the majority of the trips for the household even if they are employed full-time. Therefore, it is expected that they would spend more time traveling. The size and the structure of the household should affect travel time. Single individuals may be less likely to complete their activities outside of the home than a larger household. Income also should be influential.

⁴ In 1965, The Survey Research Center located at the University of Michigan asked 1,244 adults aged 18-64 to keep a single-day diary of activities. The combined study only made use of the national part of the data. The same Survey Research Center in Michigan used responses from 1,500 adults from one single day in the fall of 1975. The 1985 study was conducted by the Survey Research Center at the University of Maryland. Data were collected from more than 5,300 respondents aged 12 and over. This study employed the same basic open-ended diary approach as the 1965 and 1975 national studies. However, the 1985 study spread the collection of diary days across the entire calendar year. The method by which these three studies were combined was not described. The final database had 7,374 observations.

⁵ The time diaries were collected by the University of Maryland's Survey Research Center (SRC), 1,775 surveys were completed by adults aged 18 to 64 years old. All interviewing was conducted from the SRC Telephone center between April 1988 and May 2001.

As income increases, households will be more likely to purchase household services out of the home, thus potentially requiring more travel. Residential location in relation to employment centers as well as other commercial areas will also be important. Urban structure (monocentric versus polycentric cities as well as the preexisting road structure) will dictate the distance and time patterns of all trips.

Table 1.2 provides the results of a simple linear regression that investigates the impact of various factors on total daily household travel time. The data used to analyze the influences of travel time are collected from the 1995 National Personal Transportation Survey (NPTS). This survey asks study participants to record the timing, purpose, and conditions of their activity and travel behavior over a one day period. In addition, household demographic information is recorded. Travel time is distinguished from non-work travel because it is hypothesized that household factors will have differentiating influences on the two types of travel.

After controlling for the day of the week the travel diary was completed, household size, the number of vehicles, the use of public transportation, and the size of the city where the residence was located have the same significant effects on both work trips and non-work trips. As the city size increases commuting time increases. Surprisingly, income does not appear to be influential in either work or non-work travel times. Other household circumstances also appear to be influential in travel time. Households without children tend to have longer commutes but spend less time traveling for trips made for non-work purposes than households with children.

Table 1.2 Regression results; Dependent variable = log(total household travel minutes during survey day)⁶

Variable	Work Trips	Non Work Trips
Intercept	2.310 (64.07)	3.624 (132.75)
Household size	0.097 (11.91)	0.189 (36.18)
Number of vehicles in household	0.142 (17.31)	0.113 (19.56)
Daily income ⁷	0.00001* (0.39)	-0.00001* (-0.82)
No children in household 1 = no children, 0 = otherwise	0.157 (7.88)	-0.102 (-7.93)
Head of household works full-time 1 = full time, 0 = otherwise	0.462 (13.75)	-0.037* (-1.70)
Head of household works part-time ⁸ 1 = part-time, 0 = otherwise	0.216 (5.67)	-0.055 (-2.25)
Drove to location 1 = private vehicle primarily used, 0 = otherwise	-0.142 (-5.41)	-0.009* (-0.44)
Used public transportation 1 = public trans primarily used, 0 = otherwise	0.332 (7.93)	0.215 (6.89)
Walked or biked to destination 1 = private vehicle primarily used, 0 = otherwise	-0.483 (-9.72)	-0.056* (-1.45)
Lived in big city (population > 1,000,000)	0.225 (14.59)	0.064 (5.95)
Weekend 1 = survey recorded on weekend, 0 = otherwise	-0.431 (-19.56)	N/A
Sunday 1 = survey recorded on Sunday, 0 = otherwise	N/A	-0.065 (-3.49)
Monday 1 = survey recorded on Monday, 0 = otherwise	N/A	-0.029* (-1.73)
Tuesday 1 = survey recorded on Tuesday, 0 = otherwise	N/A	0.005* (0.30)
Thursday 1 = survey recorded on Thursday, 0 = otherwise	N/A	0.053 (3.12)
Friday 1 = survey recorded on Friday, 0 = otherwise	N/A	0.112 (6.35)
Saturday ⁹ 1 = survey recorded on Saturday, 0 = otherwise	N/A	0.074 (3.96)
R square	0.1052	0.1421
Number of Observations (households)	16,325	27,921

Commuting times increase for households where the head of the household works full-time, whereas the commutes for part time workers is shorter perhaps suggesting that

⁶ Insignificant coefficients are noted with an asterisk, t-statistics are in parentheses below parameters.

⁷ Daily household income was calculated as reported annual household income divided by 250 working days.

⁸ Not working is the omitted option.

⁹ Wednesday is the omitted option.

part time work may be located closer to the home. The influence of work status on non-work travel is not as clear. Part-time workers spend less time traveling for non-work travel. There are two possible explanations for this. If an individual is only working part-time, he or she has more available time to complete activities at home (i.e. cooking, cleaning, childcare, etc.) thus reducing the amount of out of home services they must purchase. In addition, part time workers are more able to spread their trip taking over non congested periods. Finally, it appears that most non-work travel takes place towards the end of the week (Thursday, Friday, and Saturday). Travel time is relatively lower on Sundays perhaps indicating the importance of the limited schedules of stores and other services rather than individual travel behavior.

In addition, the survey asked the traveler how large of a problem they thought highway congestion was, as well as unanticipated traffic delays on all roads during the course of the day. This perception of congestion is an outcome of the patterns of trip taking experienced by the individual. Therefore, these measures are treated as dependent variables in separate probit models where it is hypothesized that household attributes will influence the perception of the problems associated with congestion. The results are presented in Table 1.3.

Household circumstances appear to affect the household's perceptions of problems associated with both highway congestion and the uncertainty of traffic congestion in the same manner. The presence of young children increases the likelihood of a household being affected by congestion in comparison to those that are retired or do not have any children. This result was anticipated. The presence of children introduces a

Table 1.3 Probit results; Dependent variable = problem with congestion

Variable	Problem with highway congestion (no problem = 0, problem = 1) ¹⁰		Problem with uncertainty of traffic congestion and accidents (no problem = 0, problem = 1) ¹¹	
	Coefficients	Marginal Effects	Coefficients	Marginal Effects
Household size	-0.0476 (-4.641)	-0.0190 (-4.641)	-0.0373 (-2.297)	-0.0141 (-2.298)
Number of household vehicles	0.0798 (8.474)	0.0318 (8.475)	-0.0395 (-2.692)	-0.0147 (-2.660)
Daily Individual Income ¹²	0.00001 (0.556)	0.000005 (0.556)	0.00002 (0.766)	0.00001 (0.766)
Sex (female =1, male = 0)	-0.0680 (-4.148)	-0.0271 (-4.18)	0.06799 (2.660)	0.0266 (2.657)
No children 1 = no children, 0 = otherwise	0.0635 (2.744)	0.0253 (2.746)	-0.00005 (-0.001)	-0.00002 (-0.001)
Young children (under 5) ¹³	0.125 (3.319)	0.0496 (3.336)	0.1804 (3.037)	0.0694 (2.994)
School aged children (6-15 yrs old) ¹⁴	0.125 (3.432)	0.0496 (3.451)	0.1415 (2.486)	0.0542 (2.455)
Older children (16-21 yrs old) ¹⁵	0.0629 (1.441)	0.0250 (1.444)	0.1169 (1.718)	0.0449 (1.695)
Used automobile 1 = used auto, 0 = otherwise	-0.2239 (-8.815)	-0.0889 (-8.855)	-0.5402 (-13.584)	-0.2035 (-13.873)
Used public transportation 1= used public transportation, 0 = otherwise	-0.5423 (-11.755)	-0.2096 (-12.867)	-0.6224 (-8.790)	-0.2034 (-10.911)
Walked ¹⁶ 1 = walked, 0 = otherwise	-0.7186 (-12.095)	-0.2692 (-14.016)	-0.722 (-7.955)	-0.2269 (-10.594)
Head of household worked part-time ¹⁷	-0.0616 (-2.235)	-0.0246 (-2.235)	-0.1371 (-3.124)	-0.0508 (-3.199)
Head of household did not work	-0.4258 (-17.686)	-1.1685 (-18.016)	-0.7148 (-18.936)	-0.2532 (-21.152)
Household lived in big city ¹⁸	0.4065 (24.508)	0.1609 (24.910)	0.4591 (17.281)	0.1666 (18.184)
Pseudo R-square	0.1424		0.1346	
Number of Observations	27,966		11,456	

¹⁰ The survey question: Thinking about your day-to-day travel, please tell me if highway congestion is a large problem, a small problem, or no problem at all for you. Individuals responded on a scale of one to three, where one indicated that he or she had a large problem with congestion, and three indicated that congestion was not a problem at all. The variable was recoded such that an individual that responded with a one or two received a one for the dependent variable and individuals that recorded a three received a zero for the dependent variable.

¹¹ The survey question: Thinking about your day-to-day travel, please tell me if not knowing about traffic tie-ups or road construction is a large problem, a small problem, or no problem at all for you.

¹² Daily individual income was calculated as annual household income divided by 250 working days divided by the number of workers in the household.

¹³ This variable was equal to one if the youngest child was under 5 years old and zero otherwise.

¹⁴ This variable was equal to one if the youngest child was between 6 and 15 years old.

¹⁵ This variable was equal to one if the youngest child was between 16 and 21 years old. The youngest child over the age of 21 is the omitted option.

¹⁶ Other transportation (boat, plane, etc) is the omitted option.

¹⁷ (Do you/Does PERSON) have a job full time, part time or not at all? The head of household working full-time is the omitted option.

¹⁸ Variable was equal to one if the household live in an MSA with a population larger than one million people and zero otherwise.

set of additional time related constraints. Highway congestion or the uncertainties of congestion puts additional time pressures on the household forcing households to reallocate time.

Work schedules also appear to be influential. Non working heads of households are not as bothered by congestion. The flexibility in their schedules allows them to take their trips during non-congested periods. In addition, households that do not rely on personal automobiles consider congestion less of a problem than those who use cars. While travel using public transportation may require more time (as illustrated in the regression analysis), perhaps the stress associated with perceived congestion is not as prominent as it would be while driving. The results also indicate that congestion is not a problem for those households that walk or bike to their destinations.

For the purposes of this introduction and the remainder of the thesis, we want to evaluate the evidence available to suggest that the interaction between household structure and traffic congestion in determining travel behavior is important. Table 1.4 details the trip making behavior of the average licensed driver in a dual earner household. These data are collected from the National Personal Transportation Survey (NPTS) approximately every five years.¹⁹ Because the survey instruments are different for both the time-use studies and the transportation surveys, comparing specific findings across studies is not appropriate. Consistent general tendencies provide support for the role of changes in labor force participation on time allocation. Consistency in the total travel

¹⁹ The 2001 data were collected by the National Household Transportation Survey (NHTS) but the NHTS is the integration of two national travel surveys: the Federal Highway Administration-sponsored Nationwide Personal Transportation Survey (NPTS) and the Bureau of Transportation Statistics-sponsored American Travel Survey. At the time of this research, the 2001 raw data were not publicly available. It was only possible to collect descriptive statistics by utilizing the data tool on the NHTS website. However, these data were not available for the probit and regression analyses discussed earlier in this chapter.

time and the increases in travel time reported in both of the studies suggest that the trends displayed in these two types of surveys are important. The responses from the two surveys suggest that the time spent traveling to work has increased by 8.3% over the ten years between surveys. The travel time to non-work activities has increased rapidly as well.

Congestion occurs in areas where the population grows at a faster rate than the infrastructure used to support it. It is difficult to create a measure that provides a proxy for all effects of congestion. It is common for congestion management policies to focus primarily on the effect of congestion on the trip to work and to analyze these policies using commuting times.

Table 1.4 The average time spent traveling for all purposes, 1990 and 2001 NPTS Surveys, minutes per day, originating from the home²⁰

	1990	2001	Change (minutes)	% change
<i>Work</i>	18.89 (29,293)	20.45 (99,075)	1.56	8.3%
<i>Work related trips</i>	17.11 (1,906)	21.58 (17,439)	4.47	26.1%
<i>Shopping</i>	11.09 (27,144)	13.98 (131,955)	2.89	26.1%
<i>Other family business</i>	12.51 (31,538)	13.67 (138,695)	1.16	9.3%
<i>School/church</i>	13.88 (16,712)	16.06 (61,130)	2.18	15.7%
<i>Doctor/dentist</i>	18.04 (1,606)	19.95 (14,657)	1.91	10.6%
<i>Visit friends</i>	15.21 (13,789)	18.29 (48,536)	3.08	20.2%
<i>Other social rec</i>	15.79 (20,971)	17.35 (118,281)	1.56	2.35%
<i>Other</i>	15.69 (1,051)	19.63 (6,292)	3.94	5.58%

²⁰ These surveys were collected from the same agency. The samples are not the same and the questionnaires are not identical. However, the travel time question was available in both years. The numbers in parentheses represent the total number of trips taken for the designated purpose in each of the surveys.

Table 1.5 ranks the top ten MSA's (Metropolitan Statistical Area) in the United States by the largest increase in commuting times from 1990 to 2000. Raleigh-Durham-Chapel Hill, NC ranks first on this list, as well as two other MSA's in North Carolina that fall within the top six. The remainder of the thesis focuses on only one area, Wake County, North Carolina. This area has experienced unprecedented growth and has witnessed only the early stages of congestion.

Table 1.5 The top 10 areas with the largest increase in commuting times²¹

Region	1990 Census Commuting Time (minutes)	2000 Census Commuting Time (minutes)	% Increase
Raleigh-Durham-Chapel Hill (NC)	20.2	24.9	23%
West Palm Beach, Boca Raton (FL)	20.9	25.7	23%
Charlotte-Gastonia-Rock Hill (NC)	21.6	26.1	21%
Atlanta (GA)	26	31.2	20%
Miami-Fort Lauderdale (FL)	24.1	28.9	20%
Greensboro-Winston Salem-High Point (NC)	18.8	22.4	19%
Las Vegas (NV)	20.3	24.1	19%
Orlando (FL)	22.8	27	18%
Providence-Fall River Warwick (RI)	19.6	23.2	18%
Jacksonville (FL)	22.6	26.6	18%

1.3 Study Area Wake County, North Carolina

Wake County consists of 832 square miles. Figure 1.1 provides a map of Wake County illustrating the location of its largest municipalities. The county includes the state capital, Raleigh, and a portion of the Research Triangle Park (RTP). The RTP is home to 110

²¹ This analysis was completed by the Road Information Program. This program uses census commuting time data.

major R&D companies with approximately 38,500 employees. Overall, Wake County's population has grown by 47% between 1990 and 2000. There are two potential explanations for the increase in commuting time.

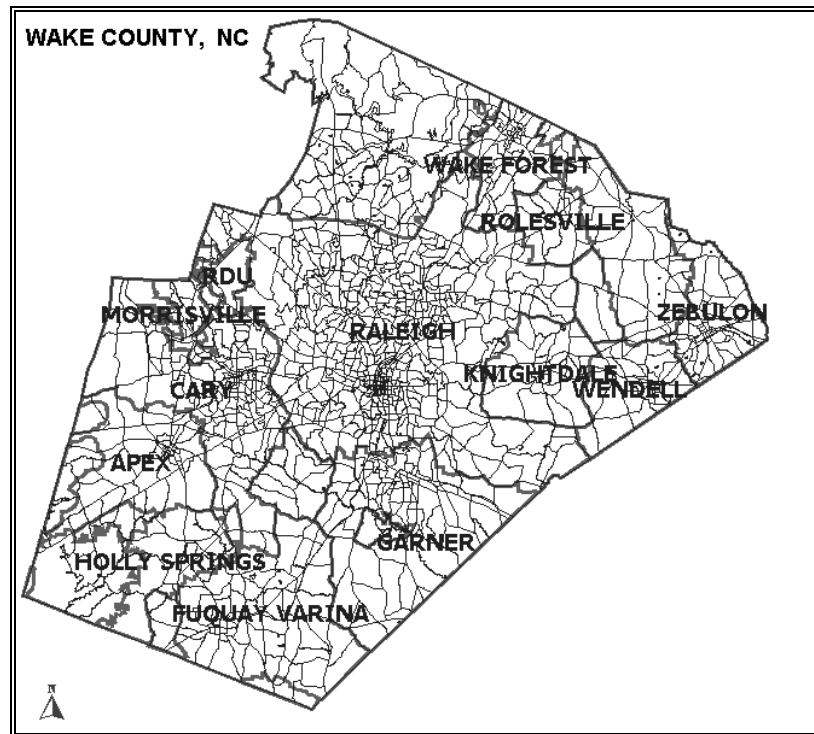


Figure 1.1 Wake County, North Carolina

First, the county has experienced considerable sprawl. There has been a tendency for households to move further away from downtown Raleigh in search of homes with larger lot sizes. Stores and services are following them outside the city to provide them with their basic household needs. These households commute greater distances than those individuals who live closer to downtown. Independent of congestion these increased distances would translate into longer travel times.

The second explanation suggests that the population has grown faster than the primary roadway's infrastructure. Two major highways serve as east/west corridors connecting different parts of Wake County to the RTP, I-40 and 70. Both of these highways have experienced significant congestion. There is future construction activity planned for widening I-40. Aside from this one initiative there are few projects planned to alleviate congestion throughout the remainder of the county. The majority of the other projects focus on maintenance.

The North Carolina Department of Transportation (NCDOT) recently completed a High Occupancy Vehicle (HOV) study for approximately fifty-eight miles of I-40. Table 1.6 reports their findings for 1998 where the last column assigns a level of service grade to that segment of the road. The level of service (LOS) grade is based on vehicle to capacity ratios. It is evident that several parts of I-40 already receive a failing grade because of the level of congestion.

Table 1.6 Current level of service grades for I-40, west of Chapel Hill to east of Raleigh, 1998^{22, 23}

I-40 Corridor Segment	Length (miles)	# Lanes	Average Daily Traffic Count	1998 LOS Grade
I-85 to US 15/US 501	11.8	4	48900	C
US 15/US 501 to NC 54	2.8	4	65600	D
NC 54 to NC 147	6.3	4	87400	F
NC 147 to I-540	3.2	6	135400	F
I-540 to Wade Avenue	6.5	8	133700	D
Wade Avenue to I/US 64/I-440	3.8	4	78500	F
US 1/US 64/I-440 to Lake Wheeler Rd	4.5	6	97800	D
Lake Wheeler Rd to I-440/I-40	4.2	8	96600	C
I-440/I-40 to US 70	4.4	6	82200	D
US 70 to NC 42	6.3	4	46000	D

²² North Carolina Department of Transportation, I-40 High Occupancy Vehicle/Congestion Management Study, Final Report, March 2003.

²³ A LOS grade of "A" indicates that congestion is low and traffic is flowing freely with low volumes and high speeds. A LOS grade of "C" indicates that congestion is moderate and that there is a stable flow of cars, but higher volumes more closely control speeds and maneuverability. A LOS grade of "D" suggests that congestion is moderate and that there are tolerable operating speeds but an unstable flow of vehicles. A LOS grade of "F" indicates severe congestion and there is a stop and go flow with long periods of stoppages.

Non-Work Related Travel

The NCDOT has focused its congestion management strategy primarily on I-40. This is the main corridor used for the trip to work. However, the number of non-work related trips has increased, causing congestion to increase in clusters around an individual's residential location and workplace, places they are likely to stop for activities both before and after work. Table 1.4, on the national level, provides evidence that travel time is increasing for non-work related trips. It is unlikely that this pattern is due exclusively to congestion. Nonetheless, congestion very likely plays a role in the additional travel time.

Table 1.7 details how the average daily traffic (ADT) count has increased in areas of Wake County that are a mix of residential and commercial communities. Downtown Raleigh is the only area where it appears that congestion has decreased. This may be an expected impact of sprawl. The appeal of visiting downtown for non-work purposes falls when substitutes are available closer to home. However, the rest of the areas have experienced a large increase in the number of cars, most notably areas near Wake Forest, Cary, and North Raleigh.

Table 1.7 The growth in traffic outside the main corridor, I – 40 ²⁴

Area	Time Period	ADT (First year)	ADT (Last year)	% Increase (per year)
Cary	1996 - 1998	13,000	21,000	20.5%
North Raleigh	1993 - 1999	3,500	10,000	26.5%
Wake Forest	1993 - 1999	3,100	9,200	28.1%
Durham/RTP	1992 - 1998	35,000	46,000	4.5%
Downtown	1992 - 1998	6,100	4,000	- 4.9%
Raleigh	1992 - 1998	9,000	14,000	7.9%
Garner	1996 - 1999	2,600	4,300	16.3%
Clayton	1995 - 1999	3,100	3,800	4.5%

²⁴ These data are collected by the NC DOT at 5,400 traffic count stations in Wake County. The counts were averaged by municipality over the time period these data were collected.

1.4. Findings

The results from this research confirm that congestion plays an important role both in long term and very short term decisions. The first essay provides preliminary evidence that travel behavior, measured through the time for the trip to work, is influenced by household constraints, as well as other demographic variables. A reduced form model indicates that several factors, such as the presence of dual earner households, the presence of young children and household size, influence the mean commuting time as well as the standard deviation of commuting time in a census block group. The results provide motivation to look beyond choices made at the aggregate spatial unit, census block group, and explore the influence of congestion on choices made on a household and on an individual basis.

In the second essay, residential location choice is modeled within a hedonic price framework arguing that these decisions are based on an expected mix of trips. The hedonic price function allows the marginal price of different types of congestion to be estimated and considers whether these proxy measures for congestion affect different households in distinct ways. Significantly negative effects of congestion are found when it is measured as an actual car count and as the household commuting time. The results are consistent with hypothesis that different types of households have distinctive types of mixes of trips that they expect to complete on a regular basis. Therefore measures of congestion should be differentially important to these household types.

The third essay measures the effect of individual and household characteristics on the impact of congestion has for the choice of non-work trips within a random utility model framework. The analysis is conducted where the time horizon is limited to a two

day period. The translation of the trip into a choice occasion has a considerable impact on the importance of household attributes and the individual's sensitivity to congestion. Individual and household characteristics such as income, age, and the number of children in the household consistently show up as important determinants on the impact of congestion on the decision to make a trip.

An approximate conversion rule is used in the last two essays to relate the marginal cost of congestion for all types of trips. This measure corresponds to linking the cost of congestion in terms of lost time. These results are summarized in Table 1.8. Annual rents fall by \$74.37 for every additional minute added to commute. This measure is presumably an extra minute of travel for every day of work because the commuting measure is the average commuting time for households living in a census tract. If we assume that one additional minute for each trip to work is added to each of the five work days, for fifty work weeks, then an individual drives 250 more minutes each year. Thus, each one of those extra commuting minutes costs approximately \$0.29.

We need to modify this approach for the congestion measure thought to encompass all types of trips, including the work trip. The results from the hedonic suggest that annual rents will fall by \$2.86 for each additional minute of travel for both work and non-work trips. Now it is assumed that each household makes one daily work trip and one daily non-work trip for a total of 500 additional minutes per year. Each additional minute would then cost about \$0.07. These two computations are now to some extent comparable to the results that are measured on a per trip basis in the RUM model.

The difference between the converted work trip measure from the hedonic and the RUM estimate is considerably larger than the difference between the all-inclusive

congestion measure and the RUM. In fact, the all-inclusive per trip cost from the hedonic falls within the range of the costs associated with only non-work trips from the RUM model. Given the different time horizons in these two models, it is difficult to make a direct comparison between the two cost measures. It is less acceptable to make comparisons about the differences between the costs associated with work trip and non-work trips. Because there is less discretion in work trips and less heterogeneity in their objective, the factors that influence the costs associated with a congested work trip will likely be much different than congested non-work trips.

Table 1.8 The marginal cost of congestion as estimated through a hedonic price model and a random utility trip choice model

	Time horizon	Marginal Cost of Additional Car	Interpretation	Marginal Cost of Additional Minute of Travel	Interpretation
Hedonic	At least the expected life of owning house	\$2.86	Annual rents would fall by \$2.86 for every additional car on the road	\$74.37 \$32.68 to \$1371.20 ²⁵	Annual rents would fall by \$74.37 for every additional minute added to the commute Annual rents would fall by a range of \$32.68 to \$1371.20 for every additional minute for both work and non-work trips.
RUM	2 day period	\$0.009 to \$0.1241 ²⁶	For every additional car on the road, the cost to an individual would range from \$0.009 to \$0.1241.	zero to \$0.11 per minute ²⁷	For every additional minute spent traveling, the cost to an individual would range from zero to \$0.11.

²⁵ This range depends on the location of the residence in Wake County and the structural road conditions, i.e. speed limit, signal light, etc.

²⁶ This range depends on the demographic group, i.e. income, age, and # children.

²⁷ This range depends on both the structural road conditions and the demographic group.

1.5. Policy Implications and Next Steps in Research

This research provides evidence that household characteristics influence both long and short term decisions. There is support for the hypothesis that there are some household circumstances that limit the members' abilities to respond to congestion. That is, the multiple time constraints on the activities that need to be undertaken, and the discretion in when they can be undertaken in relation to other commitments, limit each individual's ability to adapt to congestion. Furthermore, this study recognizes that household circumstances are also important factors driving the distribution of commuting times.

Given the results from the three essays in this paper, there remain a number of areas where future research would provide an additional understanding for the factors that influence household travel behavior and resulting congestion levels. Future research would involve investigating several closely related issues. The realization that residential and employment decisions are made jointly is an important concept that is discussed in this research but the empirical analysis does not incorporate any aspect of the labor market. The outcomes of households locating in relation to the workplace imply a commuting time to work in addition to a set of travel times for non-work activities that the household might participate in, either originating from home or from work. Incorporating a general equilibrium model that takes into consideration both the labor market as well as the housing market would provide more insight into the household's long term choices.

There are also additional considerations for short term individual behavior. There are many choices associated with trip making. The last essay discusses the implications of translating a trip into a choice and the selection of choice alternatives.

The analysis considers activity purpose and departure time as well as the two attributes in a composite definition for the alternatives individuals associate with trip taking. The next step in the research would be to include the other dimensions expected to be an important component of a trip, the trip destination and mode choice. The ability to carry out this multidimensional analysis relies on a carefully configured survey that elicits all of this information. The travel survey used in this research would not be ideal for this analysis because it requires the analyst to impute the set of choice alternatives associated with the destinations individuals visited based on only reported travel time and activity purpose. Other short term travel surveys administrated throughout the United States (Portland and San Francisco) provide this detailed information. The purpose of this analysis would be to test if different individuals choose destinations based on expected congestion at these locations. The model would attempt to incorporate all of the dimensions of a trip: purpose, mode, timing, and location, recognizing that these choices are generally not made independently of one another.

Congestion is likely to remain an important policy issue for most areas in the U.S. whether they are fully developed, rapidly growing, or in their early growth stages. All seem to be experiencing congestion in different forms. Strategies employed to deal with congestion in these areas will likely be very different. Unique structural properties, such as the road networks, residential and commercial densities, determine the spatial design of an area. However, the level of congestion will be the result of different individuals making choices both in the short and long term constrained by a set of different household circumstances. This research provides evidence that congestion is important in different ways to individuals with different household attributes who are

making trips for both work and non-work purposes. Analysts often rely on commuting behavior to guide congestion management policies. While the impact of congestion on the trip to work is important, it appears that the factors that influence how congestion alters the timing and number of non-work trips, are equally as important but often neglected.

This study area, Wake County, as well as other areas in the country that are experiencing both sprawl as well as surges in population growth, provide an interesting opportunity to gauge the potential success of congestion strategies. Sprawl generally increases the reliance on the automobile for both work and non-work trips. However, in this study area, the funding for a mass transit rail line has recently been approved. This rail line would stop at some of the major employment centers in the area.²⁸ In order for this strategy to alleviate congestion, there must be an incentive for individuals to abandon the convenience of their vehicles. Given the importance of non-work trips, a result that emerges from this research, this form of transportation must provide accessibility to both the workplace as well as non-work locations. Currently, there is very little commercial development (shopping, meals, etc) along the proposed route for this line. It is expected, given the supply of land, that businesses might recognize the potential gains from developing around this rail system. If this development occurs, individuals might be more likely to adapt to this new form of transportation. If individuals find it difficult to satisfy both their work and non-work requirements, then the rail line is unlikely to be as successful as transportation planners had expected. The success of any congestion policy

²⁸ There is currently a public bus system that makes stops at many of the same stations that will be part of the new rail line.

in an area like Wake County will be determined by how well it first meets the non-work needs of the households living in that area. Thus to enhance the prospects for the success of the rail system public authorities might consider dedicating areas along the route to commercial zones. No doubt over time the market forces will provide sources for these non-work needs. However, introducing specific incentives and locations for new businesses to locate in the zone may increase the pace that individuals switch to public transit. Designing these complementary policies will be challenging. This research provides evidence that these non-work needs are unique to the individual because of the circumstances in his or her household that dictate the constraints that other household members impose on an individual's allocation of time. For this composite strategy to be effective policymakers will need to extend this research and develop more specific insights into the services associated with the most important non-work trips.

Chapter Two

2.1 Introduction

This research considers how households' responses to congestion affect location induced differences in their commuting times to work. The analysis is based on a reduced form model. The results provide some preliminary insight on the household factors that are thought to influence commuting time. There are several key results. Commuting time decreases when young children are present in the household. Individuals in households with dual earners and school-aged children have longer commuting times, suggesting the difficulty in locating both workers in close proximity to different workplaces. The recurring hypothesis in the literature that older individuals commute less is also validated.

The conceptual logic for this model is based on the assumption that households' choices of residential and employment locations are made jointly. Households tend to sort themselves into neighborhoods based on their preferences for housing attributes with consideration for workplace attributes as well based on available housing supply across the neighborhoods. In addition, they must consider the constraints that arise from their household circumstances. If this sorting process takes place it should be possible to observe a relatively homogenous group of households living within each neighborhood given the spatial distribution of housing and employment centers they face. Thus, to the extent we can observe outcomes of this sorting behavior, such as the distribution of commuting times for each neighborhood, it is possible to test factors hypothesized to motivate that sorting are displayed as influences to this alternative reflection of the equilibrium.

The spatial unit of analysis for this research is a census block group. Census block group boundaries follow clearly visible features, such as road, rivers, and railroads, as defined by the Census. There are a maximum of nine block groups within each census tract. Census block groups are large enough that they are typically home to several hundred households. At the same time, block groups are not as aggregated as geographical units such as metropolitan statistical areas (MSA's), cities, and counties where there is greater diversity in socio-economic conditions. While individuals do not generally identify their neighborhood as their census block group, it is assumed that the block group can serve as a reasonable proxy for a cluster of similar neighborhoods. It is then expected that households, based on their preferences for the attributes the community offers as well as household constraints, will tend to sort themselves into these areas resulting in relatively homogeneous, although not identical, commuting patterns within each block group. The study area considers all the census block groups in Wake County, North Carolina.

The literature has focused on both the spatial and behavioral components of commuting behavior with varying levels of aggregated data. When data are highly aggregated, the models test primarily the influence of spatial components on average commuting time within the area. The U.S. census provides a more descriptive measure, the distribution of commuting times by census block group. This research expands the past literature by recognizing that as a result of the sorting process, the distribution of commuting times should be functions of the attributes of the individuals who locate in particular areas and the other fixed attributes associated with those areas. The analysis

tests both behavioral and socio-economic factors on the average commute time as well as the standard deviation of the commuting time distribution.

Section 2 describes the factors that are hypothesized to influence commuting time and a model to test the questions posed by them. A review of the literature comparing this study's objectives with the objectives of past research is found in Section 3. Section 4 describes the data as well as the commuting trends in the study area. Section 5 provides a summary of the results as well as tests for spatial autocorrelation. Section 6 summarizes the findings and discusses implications for future research.

2.2 Conceptual Background

The household's most important long term decisions involve residential and employment location choices. An array of personal characteristics that includes preferences for amenities in both residential and employment locations, skills, and family status play a role in these choices. The residential and employment decisions determine the day to day commute for the working individuals in the household. Because household circumstances play a decisive role in both residential and employment decisions, they will also be an indirect determinant of commuting time.

Two paradigms have been used for studying the implications of household work and residential decisions: non-structural equilibrium models and sorting equilibrium models. Rosen (1979) and Roback (1982) were the first to describe housing and labor market equilibriums as being linked to one another. They suggest that regional amenity differences are incorporated in the regional differences in both wages and land rents. Roback uses reduced form models implied by a general equilibrium framework to

estimate the implicit prices of regional amenities based on wage and land rent differentials when both markets are in equilibrium. She uses the implicit prices to construct a quality of life ranking for the 98 cities used in the analysis. Roback omits intra-city commuting time from her analysis, focusing on inter-city allocations of workers and firms.²⁹

Others have recognized the potential relationship between housing and labor markets when modeling the influence of commuting time within a non-structural framework (Merriman and Hellerstein, (1994), Waddell (1993), Simpson (1987), and So et al (2001)). Each analysis assesses the influence of commuting time as well as other origin and destination attributes on the joint decision of residential and employment locations. These studies use varying levels of data aggregation, where the unit of analysis ranges from the household to small geographic areas. With the exception of Simpson's work, the remainder of these studies explores the influence of commuting time on workplace and residential location within a discrete choice framework.³⁰

A second approach to modeling household locational decisions is through a sorting model. Sorting models assume there are a fixed number of communities, where each community conveys a unique bundle of attributes. For example, these could include amenities such as quality of education, crime, and open space. Households select a community based on preferences, income, job opportunities, housing prices, and other household characteristics.

²⁹ One of the most complete tests of Roback's framework was completed by Blomquist et al (1988). They consider many spatial, job, and housing characteristics in the analysis over a larger sample of cities. However, they also fail to consider commuting time as an important influence in both housing and job decisions.

³⁰ Simpson's analysis uses a linear regression analysis to explain workplace and residential location.

The spatial structure of the area plays a role in the sorting outcomes. The pre-existing road structure and the physical characteristics of the land will determine the accessibility of the communities in relation to other locations as well as other characterizations of urban structure. For example, the availability of public transportation, which could reflect the road network as well as the density of employment centers, could be considered an important neighborhood attribute. Households sort into communities based on observable and unobservable characteristics given the spatial structure of the area. Due to heterogeneity among households, there is not perfect stratification into communities. Instead, the sorting induces distributions across communities in income, commuting time, and housing prices that are a function of household characteristics as well as the physical properties associated with the neighborhood.

Sorting models have not typically recognized the role of employment in locational decisions and therefore have not accounted for the relationship between the housing and labor market equilibriums. It has been assumed that there is one exclusive vector of amenities associated with each community. If an area has a single central business district (CBD), then it is possible that the attributes of the workplace could easily be appended to the bundle of amenities associated with each community, because the employment center attributes should be the same for all households within each community. Thus, in this case the sorting model could be amended to consider the monocentric city. For an area with several employment districts, the sorting model becomes much more complex. Ideally, it would consider the attributes associated with the discrete choice associated with a residential location and each prospective

employment location. The attributes associated with residential location would remain the same across a set of vectors that identify the attributes associated with the different employment locations. It is not clear that a structural model could be developed that would identify parameters for polycentric areas.

If both employment and residential location factors are considered in the sorting process, then households would select a community based on the provision of local public goods as well as the attributes of the nearby employment centers. Given a set of public transportation options and a road network, these choices imply a set of outcomes for the distance and time required to get from one location to the other. Therefore, commuting behavior can be considered to be one outcome of this sorting process.

There are several equilibrium conditions associated with the outcomes of the sorting model (Epple and Sieg, 1999). Every household lives in its preferred community and no one wishes to move. In addition, communities can be ranked, and border individuals between two communities are indifferent between them. The ranking of communities by price and the measure of local public goods, as well as income will be the same. Finally, given heterogeneous preferences for the local public goods, communities are not perfectly stratified. The equilibrium implies that an outcome of sorting would be a distribution of factors important to the choice that are exogenous, or functions of exogenous variables, over each neighborhood, such as income, expenditures, etc. Specifically, there would be an implied distribution of commuting times for each neighborhood. Furthermore, this commuting time distribution should be a function of the attributes of households as well as neighborhoods.

There is a measurement issue associated with this equilibrium condition.

Congestion and commuting time are being used as equivalents, however commuting time does not necessarily indicate congestion. For a given urban structure and road network, increases in commuting time over time will mean increased congestion. Measures of congestion, including commuting time, require a baseline or a measure of commuting time in the absence of other people on the road. For a monocentric area the typical commuting time could be easily calculated. However, without information on a household's employment location in polycentric areas, the typical commuting time is generally unavailable. It is assumed that each person has a baseline commuting time, t_b , which is a function of where each member lives in relation to his or her workplace, the road network and how they commute (car or public transportation). The unobservable congestion measure would then be equal to the difference between the observed commuting time and t_b .

$$\text{Congestion} = \text{commuting time} - t_b = f(\text{household characteristics}) + \text{error}$$

Therefore, reported commuting time, which is observed, is equal to $f(\cdot) + t_b$. Congestion is considered a function of the household because it is expected that household circumstances determine the relative inflexibility in scheduling that would determine a household's ability to respond to congestion. While two households may have identical baseline commuting times, their reported commuting times may be different. The difference between the two reported times will likely be a function of the constraints each household is faced with. With complete flexibility, households would generally try to avoid congestion. However, as the scheduling of work trips, as well as other non-work

activities, becomes more rigid, the members of these households tend to be more inflexible and may be unable to avoid congestion, causing longer trip times.

Congestion, defined here as excess commuting time, is a function of the time the trip was taken. The ability of a household member to choose their departure time both to and from work may be a result of work-related choices. For example, if the employer incorporates some type of flexibility in the work schedule, then commuting times can vary while distances do not. Flexible work schedules allow employees to either postpone or arrive in advance of normal work hours. The purpose of flexibility in the work schedule is two-fold, individuals can potentially avoid congestion by arriving at work at off-peak times and it allows workers to complete activities during the typical 9 to 5 workday that ordinarily would be difficult to accomplish. There is also a notable difference in commuting times for individuals who work full-time and those who work part-time. Typically, part-time employees find work in closer proximity to their home while full-time employees drive a bit longer to their workplace.

The number of employers offering flexible work schedule is increasing over time. However, the ability to make timing choices, regardless of work scheduling flexibility, is determined by the constraints that individuals face resulting from a set of household circumstances. These additional constraints are important because individuals that do not face scheduling rigidities, resulting from the needs of other individuals within the household, are better able to adapt to commuting time by changing their departure times to reflect less congested periods. Individuals as a member of a household faced with many constraints will be less able to change their schedules because the schedules of the

others in their households may be fixed and their constraints become the relevant restrictions to observed behavior.

Hypotheses

This research hypothesizes that household and other demographic factors which serve as proxies for the level of household responsibility should be considered determinants of commuting time. These times are the outcomes of households locating in relation to their workplace. It is hypothesized that family preferences will play a key role in commuting behavior. Marital status and the presence of children, specifically the age of children will play a role in determining commuting time. Additional household factors that create time pressures will inevitably constrain choices and may be determinants of household commuting patterns. Single individuals generally will face the smallest number of time constraints. As a result, they may be able to adapt more readily to long commuting times by switching departure times or in the long run switching residential or employment locations. They also may find it easiest to locate in close proximity to their workplace because they do not need to take into consideration the preferences of others.

Married couples, particularly dual earner households, with children face an entirely different set of constraints. It is difficult to minimize commuting times when there are dual earners working in different locations. The presence of children, especially young children, has a tendency to locate one of the parent's workplaces, typically the mother's, closer to the home. However, once the children get older, this may not be an issue. If a household only has a single earner, then the commuting behavior of the one worker will again be different from the other household types.

Other attributes such as age, the access to personal transportation, and race are also hypothesized to limit flexibility. Older individuals may face physical impairments, such as fatigue or poor eyesight, limiting their time to travel. In addition, individuals who are forced to use public transportation are faced with very rigid schedules that limit both the time of day, and the day of the week to travel.

2.3 Literature Review

The existing literature generally has considered the influences of urban structure and personal characteristics on commuting time separately. This dichotomy in the models and the resulting tests contradicts the assumptions of the sorting model. Households select communities based on their preferences and other family characteristics, given the spatial structure specific to an area that includes residential neighborhoods and employment centers. Therefore, these two factors should not be considered independently as they are both hypothesized to be important influences of commuting times. However, because the literature treats the spatial components of commuting time separately from the behavioral components, the literature review highlights the findings from each of these separate strategies.

The unit of analysis also differs between the two strands of research. The influences of urban structure on commuting times are generally tested with highly aggregated data such as mean commuting times from MSA's, city, etc. Individuals living within a large area are generally going to be heterogeneous. Therefore, using one measure to indicate the typical commute (i.e. the mean commuting time) for everyone masks variability in behavior based on household choices. The second strand literature

considers the influences of household circumstances on commuting behavior, consistently measured at the individual level. This formulation may be too disaggregated because the analyst has limited information on the employment and residential choices facing the household.

Spatial Components of Commuting

Gordon et al (1989), Schwanen et al (2002), and Guiliano and Small (1993) all attempt to explain commuting behavior by the degree of polycentricity, measured by housing and employment densities, population growth, or some indication of worker-to-job ratios. The results are not entirely conclusive across these three studies. Gordon et al find some evidence that polycentricity reduces commuting time. Schwanen et al agree with that conclusion, but suggest that jobs-housing balance is required in the suburbs. If this is not the case then polycentricity does not decrease commuting times because people have to travel across other suburbs to find employment. Guiliano and Small test for the importance of the jobs-housing balance. They find that while it is significant, it is not a very important influence on commuting time.

Bento et al (2004), using micro-level data, test for the effect of jobs-housing balance as well as other measures of urban form on commuting mode choice and the household's vehicle miles traveled. They find that their measure of jobs-housing balance had an influence on the mode used to commute to work. Specifically, a greater jobs-housing balance increased the probability of using non-motorized methods for travel. Furthermore, the authors conclude that an increase in the jobs-housing balance increases the number of vehicle miles traveled for one-vehicle households, but the effect is small.

This variable has no influence on households with more than one car. Table 2.1 summarizes the specific findings in these four studies.

Table 2.1 Spatial determinants of commuting time

Authors	Unit of Analysis	Location	Variables Tested	Key Results
Gordon, Kumar and Richardson (1989)	City	32 Cities in U.S.	Dependent Variable = mean commuting time Independent variable = Density, economic structure, polycentricity, income measures and carpooling	1) Monocentricity adds to commuting time 2) Higher incomes result in lower commuting time 3) Higher residential and commercial density increase commuting time while higher industrial density reduces it.
Schwanen, Dielman, and Dijst (2002)	Multiple levels- Individual, municipality, and metropolitan area	Netherlands	Dependent Variable = individual commuting time Independent Variables = Household variables, 3 density measures (municipality), metro size, density, employment and population growth	1) The main effects of household structure are small (single workers commute more than those with a partner, women in households with children commute less) 2) Commute time is not impacted by employment density 3) Partial evidence that drivers in polycentric regions commute less than residents of monocentric regions.
Guiliano and Small (1993)	Transportation Analysis Zones	1146 zones in Los Angeles	Dependent Variable = mean commute time Independent Variable= Worker-Job ratio	1) There is a negative relationship between the worker-job ratio and average commuting time 2) Jobs housing balance measured by the ratio of resident workers per job has a statistically significant, but not very large, influence on time.
Bento, Cropper, Mobarak, and Vinha (2004)	Municipalities	114 cities in the United States	Dependent Variable = Mode and Vehicle Miles Traveled Independent Variable = jobs-housing balance	1) Only population centrality has a significant impact on car ownership. 2) An increase in jobs housing balance has a positive effect on a household's vehicle miles driven.

Behavioral Components of Commuting

The literature considering the behavioral determinants of commuting patterns has found that several characteristics dominate as influences of commuting time. Table 2.2 provides a summary of the major findings relating household composition, age, and race to commuting time. Most of the inconsistencies in this strand of literature occur when

testing for the influence of household responsibility on commuting time. The household responsibility hypothesis (HRH) suggests that employed women tend to have greater household and child-care responsibilities and therefore face greater time pressures and will choose shorter commutes than employed men (Johnston-Anumonwo, 1992). Many variables have been used to test for the HRH, for example, simple gender differences, marital status, and the presence, number and age of children.

Table 2.2 The behavioral components of commuting time

	Authors	Study Area	Type of trip	Variables Tested	Key Results
Household Responsibility Theory & Gender Differential in Commuting	Pazy, Salomon, Pintzov (1996)	Tel-Aviv Israel	Work Trip	Career factors, Family Factors, Work trip factors	Women separate their family and work roles
	Lee and McDonald (2003)	Seoul, Korea	Work Trip	Education, marital status, children, age	Commute time for married females not significantly different than non-married females.
	White (1986)	New York City	Work Trip	Income, taste and demographic factors	The presence of young children has a POSITIVE effect on commute time.
	Turner and Niemeier (1997)	National	Work Trip	Marital status, #	Presence of children and marital status have small but significantly negative effect on commuting time
Age	Raitanen et al (2003)	Finland, Germany, and Italy	Work and Non-work Trips	Individual and household demographics, opinions towards driving	Older individuals drive with lower frequency, fewer kilometers. And they try to avoid certain types of traffic situations (congested time periods, construction, etc)
Race	Gabriel and Rosenthal (1996)	United States	Work Trip	Education, age, sex, marital status, other workers in household	Blacks commute just under 14% longer. But the black commute premia differ with the worker's education.
	Guiliano (2003)	United State	Work and Non-work Trips	Gender, age, income, employment status, metropolitan location, neighborhood characteristics	Gender, age, and income do not have the same effect on travel across race groups.
Mixed Studies	Schwanen, Dijst, Dieleman (2002)	Netherlands	Work and Non-work Trips	Sex, age, education, dual earner	Time to work – workers in traditional families commute longer than dual earner families

The inconsistencies are evident when looking specifically at the importance of the presence of children on commuting times. White (1988) finds that the presence of young children has a large positive effect on commuting time whereas others provide evidence that the opposite is true (Lee and McDonald (2003) and Turner and Neimeier (1997)). Pazy et al (1996) suggest that women are beginning to separate home life from their careers. Their study concludes that women are now willing to commute longer to enhance their career.

A common finding observes that older individuals, those at retirement age or older, commute much less and on whole, drive fewer miles for all types of trips. Raitanen et al (2003) find that older individuals drive fewer miles for several reasons: trying to avoid certain types of traffic situations, environmental and personal reasons, health conditions, difficulties in finding a parking space, and as a result of efforts to avoid stressful travel conditions. Moreover, the employment decisions of older individuals will determine the length of their commute. While older individuals typically retire from full-time work at ages between 55 and 65, they frequently work part-time. Their part-time jobs are generally closer to the home resulting in a shorter commute.

Racial and ethnic factors also appear to play a role in commuting time. Gabriel and Rosenthal (1996) cite that minority workers face restricted residential and employment opportunities because of discrimination in both the housing and labor markets. These factors create a spatial mismatch between where minorities live and where the jobs are located causing longer commuting distances and times. The authors find that black individuals commute just under 14% longer than white individuals. However, education plays a large role in determining the length of the commute. For

black individuals with a high school degree, their commute is 22% longer and for black individuals with a college degree their commute is 15% longer, but for blacks without a high school degree there is no difference in commuting times from white individuals with the same education. Giuliano (2003) also finds that gender, age, and income do not have the same effect on travel across race groups.

The literature displays considerable agreement on several factors that influence commuting time. However, there does not appear to be a clear conclusion on the effects of household responsibility measured by the number and age of children in the household, as well as urban structure, on commuting behavior.

This study considers the potential sources of discrepancies in the past findings. The first arises with the spatial unit of analysis and its role in determining the influences of commuting time. When data are highly aggregated as was the case in the urban structure studies, the individuals within that area may well be so heterogeneous that one single measure (i.e. the mean commuting time) can not accurately capture the hypothesized influences of urban spatial structure. The micro level is not necessarily optimal either. The analyst usually only has information on where people reside in relation to their workplaces, as measured by the reported commuting time. Unfortunately, the set of choice alternatives describing where individuals work and live is unknown.

This research considers a unit of analysis that is approximately equivalent to a neighborhood. Outcomes at the aggregate level are observed as distributions of similar, but not identical, households making locational choices in relation to their workplace. While this study does not currently examine these outcomes as the full distribution, it

does utilize several characterizations of the distribution of commuting time (the mean and standard deviation).

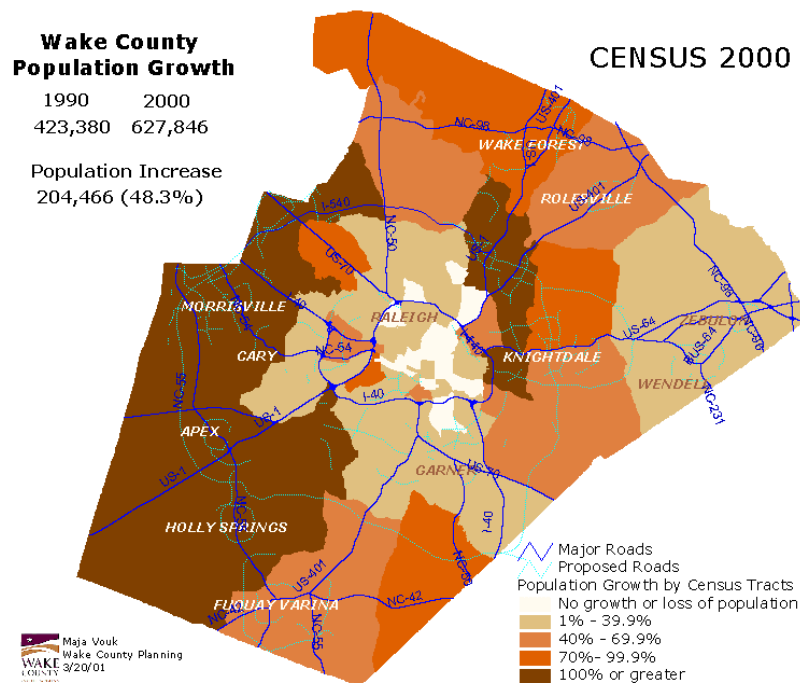


Figure 2.1 Wake County population growth by city/town

2.4 Data

The study area, Wake County, NC, has changed from an area that was at one time monocentric, where the CBD was located in downtown Raleigh, to polycentric, where relatively dense employment centers are located in several areas of the county. In addition to this change in the distribution of employment centers, there has been a shift in the distribution of residential locations towards locations outside the city, resulting in sprawl. The large population growth and changing spatial structure makes Wake County an interesting case study. The major cities and towns in Wake County are illustrated in

Figure 2.1. In addition, the shading of the figure depicts the large population growth between 1990 and 2000 in the area. Rapid growth is particularly pronounced for areas outside of downtown Raleigh.

This study will test the effects of both urban and behavioral components on the distributions for commuting time across block groups. The analysis requires data that characterizes households, as well as household circumstances that are likely to affect the spread between the reported commuting time and commuting time in the absence of congestion such that

$$\begin{aligned} \text{Excess Commuting Time} &= \text{Reported Commuting time} - t_b \\ &= f(\text{household characteristics}) + \text{error}. \end{aligned}$$

Furthermore, measures that describe the neighborhood are also needed, for example, variables that reflect the level of polycentricity in the area, such as density and the availability and use of public transportation. Finally, a price index for a constant quality unit of housing is also important.

These measures are not all available from the same data set. Data are combined from several different sources: The U.S. Census, Wake County road networks supplied by the 2000 Census Tiger/Line Files, and records of housing transactions that describe the sales price and the structural properties of the house. Each data set will be described in detail as well as the method by which all the data were combined.

The 2000 U.S. Census provides information on household socio-economic and demographic variables as well as information on the distribution of commuting times at the census block group level. Of the 272 census block groups in Wake County, there

were a total of 262 census block groups that provided information on all of the variables used in the estimation.

The raw data describing commuting time is represented as the number of households within each block group that had a reported one-way commuting time within a specified time interval.³¹ There are techniques that would allow the choices to be represented in terms of distributions of commuting time by census block group. These require a distribution be assumed and face identification questions in distinguishing the role of independent variables for measures of the location and scale parameters. As a result, this analysis uses the mean and standard deviation of the distribution to analyze the factors influencing commuting times across neighborhoods. Given that commuting times are always non-negative, the means and standard deviations for commuting times for each block group are estimated from a lognormal distribution given the commuting time intervals.³² This procedure closely follows Stewart's (1983) maximum likelihood estimator that observed the dependent variable as falling within certain continuous intervals.³³

Assume that C_i^* is the true but unobserved logarithm of commuting time for $i = 1, \dots, N$ communities. C_i is the observed category with known end point values which includes the unobserved C_i^* . We observe $C_i = j$ for $j = 0, \dots, J$ if $A_{j-1} < C_i^* < A_j$,

³¹ Commuting time was measured as the travel time to work for workers 16 years and older.

³² Assigning the midpoint of each interval as the mean commuting time for each census block is not optimal because it may result in inconsistent model relationships (Hsiao, 1983)

³³ Others have expanded on this methodology to allow for missing grouped data observations (Bhat, 1994) as well as heteroscedasticity (Caudill and Jackson (1993)).

where A_j is the natural log of the original category boundaries. Then the probability that

C_i^* falls in the j^{th} category, is given by

$$(2.1) \quad P(C_i = j) = P(A_{j-1} < C_i^* < A_j) = \Phi[(A_j - \mu_{C_i}) / \sigma_{C_i}] - \Phi[(A_{j-1} - \mu_{C_i}) / \sigma_{C_i}]$$

where Φ is the standard normal cumulative distribution function. For an independent

random sample of N observations, the log likelihood function is the sum of these

probabilities taken across the J categories and over the n observations (2.2) where δ_{ij} is

the number of households within the i^{th} community that have an observed commuting time within the j^{th} category and 0 otherwise.

$$(2.2) \quad LLF = \sum_{i=1}^N \sum_{j=1}^J \delta_{ij} \ln \left[\Phi \left(\frac{A_j - \mu_{C_i}}{\sigma_{C_i}} \right) - \Phi \left(\frac{A_{j-1} - \mu_{C_i}}{\sigma_{C_i}} \right) \right].$$

The resulting maximum likelihood estimates of μ_{C_i} and σ_{C_i} , $mean_c_i$ and std_c_i respectively in terms of logs, are separately defined as dependent variables.

Figure 2.2 illustrates the average commuting time for households across census block groups. From the map it is possible to speculate about the location of employment from the commuting behavior of households in each census block group. Households living in census block groups close to downtown Raleigh have a short commute, implying that many households may work in downtown Raleigh. Households in census blocks outside the perimeter of downtown appear to have much longer commutes, suggesting that many households are migrating out of the county towards the RTP.

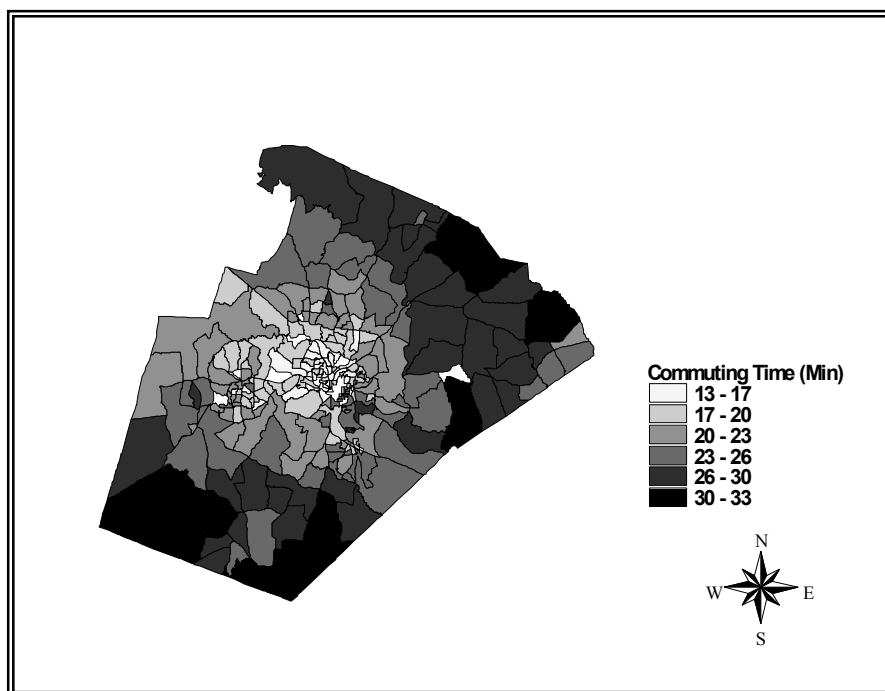


Figure 2.2 Wake County average commute time 2000 (census block group)

The census also provides data on the distributions of other variables, specifically income and age, as well as information on household size, household type, and the presence and age of children in the household. The mean of income is calculated using the same methodology as discussed previously for imputing the mean of commuting times. Therefore, income is in log form as well. The census also supplies data characterizing the neighborhood, such as the number of housing units and the availability and use of public transportation.

To construct a variable that best approximates one dimension of urban structure, housing density in relation to the road infrastructure, a neighborhood characterization, the count of housing units in each census block group was normalized by the total number of road feet within each census block group. Total road feet were calculated as the sum of both primary and secondary roads in each census block group provided by the 2000

Census Tiger/Line files. Figure 2.3 illustrates the variation in housing densities per road mile over census block groups.

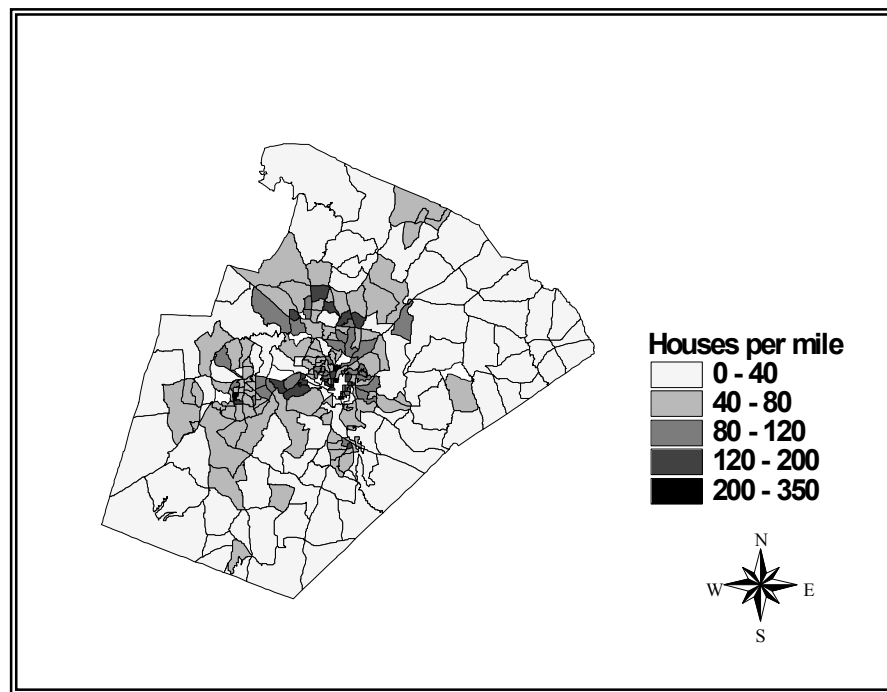


Figure 2.3 Houses per mile of road

Housing prices play a key role in locational equilibrium models. They determine the implicit costs of the bundle of amenities each community offers. Houses are heterogeneous. Price indexes that do not control for quality differentials are likely to be inaccurate. Bailey et al (1963) use a regression analysis to control for quality differences in the construction of a time-varying housing price index by including fixed effects for the year of sale. This process allows us to develop a single index for the location specific attributes that influence sales prices. More specifically, with micro data on the sales prices of homes and their characteristics, it is possible to estimate how location specific factors contribute to equilibrium prices. The logic requires that the model control for the

role of the individual characteristics of each home in influencing prices. Assuming these location specific attributes have the same effects for all homes in a market are it is possible to use the indexes to reflect the effects of these factors without including measures of the characteristics of the heterogeneous housing within a jurisdiction. In this study, fixed effect coefficients estimated from a hedonic price analysis were used in the construction of a housing price index that controlled for quality adjusted housing prices.

Housing markets are defined by multiple listing service (MLS) zones that are composed of census block groups.³⁴ The MLS is a group of brokers joined together for the purpose of pooling their respective property listings. If a property is sold by any member of the service, other than the listing broker, the commission is divided between the listing broker and the selling broker who brings upon the sale.

The housing data, consisting of single family homes sold between 1992 and 1999, were purchased from a commercial vendor, Transamerica Intellitech. Each record includes the structural properties of each home, i.e. bathrooms, square footage, etc, was attached to the record of sale. Fixed effects representing the nineteen MLS zones in Wake County were included in the estimation of a semi-log function as the hedonic pricing model. The hedonic also tests the influence of the structural properties of the home on housing prices. The full set of results can be found in Appendix A. All of the characteristics of the house were significant with the anticipated sign and 13 of the 18 MLS fixed effects were significant. The exponentials of the estimated coefficients for the MLS zones were used to develop the housing price index fixed effects.

³⁴ MLS zones are determined by the board of realtors based on what they believe best represents a housing market. The definition of an MLS zone was extracted from the Encyclopedia of Real Estate Terms.

A census block group was assigned an MLS price if the census block group was geographically located within that MLS zone. If a census block group intersected two or more MLS zones, the MLS zone that contained the majority of the census block group's land area was selected. Table 2.3 provides a summary of the number of census block groups that fell within each MLS zone. Figure 2.4 displays how the housing price index varies over the census MLS zones in Wake County. From this illustration, it is evident that the higher priced housing is located in Western Wake County and just north of downtown Raleigh, whereas the lower priced housing is located on the eastern boundary of the county.

Combining the census data, the information on the road network, and price indexes from individual housing transactions within Wake County, the final database provides a characterization of households and the neighborhoods they live in, as well as the resulting commuting times. Descriptive statistics for these variables are reported in Table 2.4.

Table 2.3 The number of census block groups within each MLS zone

MLS Zone	1	2	3	4	5	6	7	8	9	10
# Census Block Groups	44	32	29	15	35	18	10	6	9	6
Price Index	1.284	1.015	0.858	0.992	1.036	0.913	1.021	0.990	1.057	1.084
MLS Zone	11	12	13	14	15	16	17	18	21	
# Census Block Groups	8	6	6	8	4	10	3	3	7	
Price Index	0.979	0.895	0.862	1.010	1.031	0.954	0.975	0.990	1	

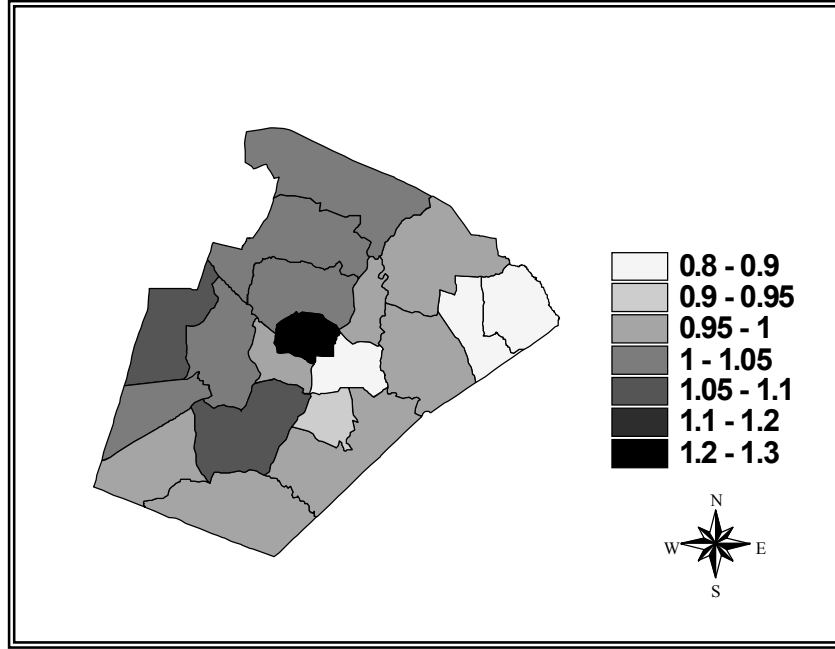


Figure 2.4 Wake County housing price index (MLS zone)

2.5 Empirical Analysis

The general estimation strategy is to test the influence of household and neighborhood characteristics, factors likely to be important determinants of residential location, on different characterizations of the distribution of commuting times, one of the outcomes of household sorting. Specifically, the analysis estimates the following two equations:

$$(2.3) \quad \text{mean}(\log_c_i) = x_i\beta + \varepsilon_i$$

$$(2.4) \quad \text{std}(\log_c_i) = x_i\delta + \mu_i$$

x_i is a vector of both neighborhood and household characteristics hypothesized to affect the mean and standard deviation in the i^{th} census block group for $i = 1, \dots, N$. ε_i and μ_i are both random error terms with mean zero and variance σ^2 .

Table 2.4 Census block group descriptive statistics

Variables	Mean	Standard Deviation	Minimum	Maximum
Characterizations of the Household				
Average number of households	923	721	19	4,736
Income ³⁵	\$52,506	\$21,815	\$6,861	\$138,275
Household size	2.48	0.38	1.21	3.29
% of White Households	71.7%	24.6%	1%	99.5%
% of African American Households	22.3%	24.3%	0	98.7%
% of households with head of household older than 65 years old	14.4%	9.4%	1.9%	55.8%
% households with Children under 6 years old	13.4%	6.9%	0%	50%
% Dual Earner Households with Children under 6 years old	40.6%	21.9%	0	100%
% Dual Earner Households with Children between 6 and 17 years old	64.5%	22.3%	0	100%
Neighborhood Characteristics				
Housing Density (housing units per mile of road)	62.54	47.78	8.34	328.21
% households using public transportation	1.9%	4.9%	0	40.8%
Observed Outcomes³⁶				
Commute time (minutes)	21.96	4.40	13.18	32.35
Commute time standard deviation (minutes)	2.04	0.34	1.33	4.70

These two equations are initially estimated with ordinary least squares (OLS).

However, OLS will produce inconsistent estimates if the housing price index included is endogenous. The concerns for endogeneity arise because the price of a house is determined as a result of the market equilibrium that arises from the sorting of households. It is reasonable to expect the price indexes are likely to be correlated with

³⁵ Income is reported as a dollar amount in this table for illustrative purposes only. The remainder of the analysis maintains that income is in log form.

³⁶ For illustrative purposes only, the statistics reported here are transformed from the lognormal estimates of the mean and standard deviation of commuting times by taking the exponential of the lognormal estimates. The remainder of the analysis maintains that the mean and standard deviation are estimated from a lognormal distribution and are not transformed.

unobserved household and neighborhood characteristics. To take account of this possibility, the second step in the estimation process tests for endogeneity and corrects for it by implementing a two stage least squares (2SLS) estimator based on the test outcomes. Finally, unobserved heterogeneity in households as well as potentially omitted variables describing the neighborhood can give rise to spatial correlation across block groups. Thus, the analysis considers the potential for spatial autocorrelation as well.

Each of these issues is discussed separately in the analysis. In the instance when both endogeneity and spatial autocorrelation are present, the analysis will utilize an estimator that simultaneously addresses both issues.

OLS estimation

The results from regressing household and neighborhood characteristics on the four characterizations of the distribution of commuting time are presented in Table 2.5. All variables are significant in Model 1 with the exception of the median contract rent as well as the percentage of black households and the percentage of individuals between the ages of forty-five and fifty-four living in each census block group.

Because income is in log form, the coefficient can be interpreted as an elasticity. For a 1% increase in income, commuting time will increase by 7.2%. Circumstances that were hypothesized to potentially limit a household's scheduling flexibility are of the expected sign. In general, it appears that older individuals commute less either because they have retired from the workforce altogether or are working part-time in close proximity to their residential location. The presence of other age groups also appears to be influential. The presence of younger adults (ages between eighteen and thirty-four)

significantly reduces the mean commuting time. Older age groups (35- 44 years old and 55 – 64 years old) significantly increase the mean commuting time.

As the percentage of households with young children increases within each community, commuting time decreases. This variable is only marginally significant. It reflects the need for one parent to work in close proximity to the home for the purposes of being available to his or her children. For areas with a large percentage of dual earner families with school aged children, commuting time increases. With children in school, there is an increased flexibility in the parent's schedule and this could create additional employment opportunities that may be further away from the home.

The influence of neighborhood characteristics on commuting time is tested through the housing density measure and the use of public transportation in each census block group. Neighborhoods with higher density levels appear to have a negative effect on commuting time. In Wake County, the density measure is greatest around downtown Raleigh (Figure 2.3), but commuting times are also the lowest in that area (Figure 2.2). Thus, it appears that housing density is not necessarily a proxy for congested roads, but instead it is potentially a measure of accessibility to the workplace. Finally, the use of public transportation has a positive effect on commuting times. Currently, buses are the only available mode of public transportation in the study area. They typically take longer because of the number of stops, route plans, and scheduling rigidities.

Table 2.5 Ordinary least squares results ³⁷

Model 1	$y = \text{mean}(\log_c_i)$	Model 2	$y = \text{std}(\log_c_i)$
Intercept	1.8631 (4.292)	Intercept	1.324 (4.944)
Log Mean Income	0.0720 (1.681)	Log Mean Income	-0.0747 (3.011)
% Individuals with graduate degree	-1.1111 (-8.759)	% White households	0.0726 (1.698)
% Black households	-0.0604 (-1.122)	% Black households	-0.0233 (-0.409)
% Between 18 and 24 years old	-0.0334 (-1.784)	% American Indian households	0.1814 (0.159)
% Between 25 and 34 years old	-0.4791 (-2.649)	% Asian households	-0.6677 (-2.745)
% Between 35 and 44 years old	0.8329 (3.043)	% Between 18 and 24 years old	-0.0191 (-1.223)
% Between 45 and 54 years old	0.2254 (1.284)	% Between 25 and 34 years old	0.3024 (2.152)
% Between 55 and 64 years old	0.2921 (2.201)	% Between 35 and 44 years old	-0.5490 (-2.304)
% Older than 65 years old	-0.2938 (-2.818)	% Between 45 and 54 years old	0.0987 (0.648)
Average household size	0.1337 (3.973)	% Between 55 and 64 years old	-0.1474 (-0.963)
% Households with young children	-0.1184 (-1.850)	% Older than 65 years old	0.1777 (2.406)
% Dual earner households children between 6 and 17	0.1059 (2.907)	Variance in household size	0.0313 (2.350)
Housing price index	0.3174 (4.711)	Housing price index	0.0469 (0.891)
Median housing rent	-0.00004 (-1.272)	Median housing rent	-0.00001 (-0.442)
Housing units per foot of road	-3.075 (-2.926)		
% Using public transportation	0.4809 (2.133)		
	$R^2 = 0.693$		$R^2 = 0.215$

A different selection of variables is included in Model 2 to test the factors hypothesized to influence the log standard deviation of commuting time within the census block groups. The distribution of race within each census block group was included. As a result, the presence of white and Asian households has a significant effect on the

³⁷ t-statistics are in parentheses below estimate. Significant estimates for $\alpha = 0.10$ are in bold.

standard deviation of commuting time. In addition, several of the age groups are also influential. Income has a significant effect on the standard deviation of commuting times as well. For a 1% increase in income, the standard deviation of commuting times will fall by approximately 7.4%. This could suggest that households with higher income in the same neighborhood may be traveling to the same workplace and experiencing a relatively similar commuting time. Finally, a variable for household size variance was also included. It was expected that as the variance in household size within an area increases, variability in commuting times should increase as well. The significantly positive coefficient validates this hypothesis. The R-square is lower for this model. The model might better be explained if additional data were available that might better describe the variability of different household factors in each census block group beyond race, age, and household size.

Endogenous Housing Prices

The value of a house and any other neighborhood attributes determined by the sorting of households, including commuting time, are likely to be correlated with unobserved household and neighborhood attributes. This relationship is made particularly clear when we review the measurement issues associated with the commuting time variable. t_b , the baseline measure of commuting time in the absence of congestion, is a latent variable. It may be correlated with unobserved household characteristics. In this model, it is part of the error, therefore, it is expected that the price index will be correlated with these household characteristics.

Table 2.6 Two stage least squares results^{38, 39}

Variable	Model 1 $y = \text{mean}(\log_c_i)$
Intercept	0.8356 (4.211)
Log Mean Income	0.0726 (1.696)
% Individuals with graduate degree	-1.1064 (-8.709)
% Black households	-0.0566 (-1.046)
% Between 18 and 24 years old	-0.0334 (-1.788)
% Between 25 and 34 years old	-0.4735 (-2.616)
% Between 35 and 44 years old	0.8312 (3.036)
% Between 45 and 54 years old	0.2280 (1.298)
% Between 55 and 64 years old	0.2961 (2.228)
% Older than 65 years old	-0.2945 (-2.825)
Average household size	0.1329 (3.946)
% Households with young children	-0.1174 (-1.838)
% Dual earner households children between 6 and 17	0.1062 (2.917)
Housing price index	0.3854 (4.668)
Median housing rent	-0.00004 (-1.243)
Housing units per foot of road	-3.0464 (-2.896)
% Using public transportation	0.4869 (2.158)
Hausman test statistic	2.576

³⁸ t-statistics are in parentheses below estimate. Significant results are in bold.

³⁹ The Hausman t test: $t = \frac{\hat{\beta}_{iv} - \hat{\beta}_{ols}}{\sqrt{Var(\hat{\beta}_{iv} - \hat{\beta}_{ols})}}$

The sorting model implies housing prices should be ordered consistent with amenities and income. Housing prices determine the rank of a community within an area. Thus, the price rankings that order communities by housing price from highest to lowest are used as instruments. Both the price rankings and the polynomial of the price rankings are highly correlated with the price index and uncorrelated with commuting time, satisfying the requirements of a good instrument. Estimation is completed with 2SLS. A Hausman test is implemented for each of the two models to determine if the housing price index is endogenous. The price index variable is found to be endogenous for the given set of instruments only when the dependent variable is measured as the mean of the log of commuting time.⁴⁰ The results are presented in Table 2.6. All of the two stage least squares estimates remain the same sign and significance as the OLS estimates.

Spatial Autocorrelation

The measurement issues associated with the commuting time variable give rise to an additional econometric issue. The baseline measure of commuting time was hypothesized to be part of the error. In addition, it is also a function of unobserved heterogeneity. It is likely that both unobserved household and neighborhood characteristics are shared over adjacent geographical areas. This is particularly relevant for this study because the boundaries of a census block group are defined by the Census by the physical properties of the area (i.e. roads, rivers, railroads). This is considered a reasonable proxy for a neighborhood but true neighborhoods, as households would

⁴⁰ Because the commuting data are reported from households that may either own or rent their houses, the specification also includes the median contract rent in each census block group. Rents are likely to move in the same direction as housing prices. Thus, only housing prices are instrumented in this model.

describe them, may span over census block group borders. Furthermore, there are several spatial components that are hypothesized to affect commuting time discussed in the literature review that could not be included in this study because of data availability. These circumstances suggest that it would not be surprising to find that the errors are spatially correlated. Spatially correlated errors do not result in biased estimates but failing to correct for them does produce inefficient estimates and biased standard errors.

The test for spatial autocorrelation requires the specification of a weighting matrix. The weighting matrix determines the strength of the spatial relationship between one spatial unit and its neighbor(s). W is an $n \times n$ matrix where n equals the total number of census block groups. $w_{ij} = 1$ if the i^{th} census block group shares a border with the j^{th} census block group and $w_{ij} = 0$ if $i = j$ or if i and j don't share a border. The matrix is row-standardized such that $W_{ij} = w_{ij} / \sum_i w_{ij}$.

One approach to estimating the spatial autocorrelation parameter, ρ , is with a generalized moments estimator (Kelejian and Prucha (1999)). Given a weighting matrix, W , the estimation of ρ is based on minimizing the three moments of the error term. A discussion of the full estimation procedure is located in Appendix B. When the dependent variable is measured as the standard deviation this estimation approach is appropriate. However, when the dependent variable is measured as the mean commuting time, there must be a simultaneous correction for endogeneity and spatial autocorrelation. A three-step procedure is used that is similar to the method introduced by Kelejian and Prucha (1998) and applied in my earlier work (2004). In this application, a spatially lagged dependent variable is replaced with the endogenous housing price index variable.

Table 2.7 Results from incorporating spatial autocorrelation⁴¹

<u>Model 1</u> Two-Stage Generalized Least Squares	$y = mean(\log_c_i)$	<u>Model 2</u> Generalized Least Squares	$y = std(\log_c_i)$
Intercept	1.8737 (4.365)	Intercept	0.3864 (5.468)
Log Mean Income	0.072 (1.737)	Log Mean Income	-0.0784 (-3.372)
% Individuals with graduate degree	-1.0475 (-8.033)	% White households	0.0377 (0.935)
% Black households	-0.607 (-1.097)	% Black households	-0.0245 (-0.478)
% Between 18 and 24 years old	-0.0279 (-1.606)	% American Indian households	-0.0084 (-0.009)
% Between 25 and 34 years old	-0.4537 (2.673)	% Asian households	-0.5156 (-2.329)
% Between 35 and 44 years old	0.7780 (3.063)	% Between 18 and 24 years old	0.0097 (-0.710)
% Between 45 and 54 years old	0.1973 (1.211)	% Between 25 and 34 years old	-0.1676 (1.259)
% Between 55 and 64 years old	0.2505 (2.063)	% Between 35 and 44 years old	-0.4439 (-2.079)
% Older than 65 years old	-0.2656 (-2.501)	% Between 45 and 54 years old	0.1514 (1.118)
Average household size	0.1244 (3.930)	% Between 55 and 64 years old	-0.1297 (-0.964)
% Households with young children	-0.1090 (-1.809)	% Older than 65 years old	0.0747 (1.041)
% Dual earner households children between 6 and 17	0.1030 (3.092)	Variance in household size	0.0311 (2.665)
Housing price index	0.3331 (3.821)	Housing price index	0.0412 (0.671)
Median housing rent	-0.000003 (-1.252)	Median housing rent	-0.0001 (0.468)
Housing units per foot of road	-2.963 (-2.956)		
% Using public transportation	0.4654 (2.092)		
Spatial Autocorrelation Parameter	0.3540	Spatial Autocorrelation Parameter	0.4435
Moran I statistic	5.308 (p<.0001)	Moran I statistic	7.466 (p<.0001)

⁴¹ t-statistics are in parentheses below estimate. Significant estimates are in bold.

The details of this estimator can be found in Appendix C. The autocorrelation parameter and resulting parameters estimated for both models are located in Table 2.7. The results from the Moran's I test indicate the presence of spatial autocorrelation for both models.

In Model 1, only the variable indicating the presence of 18 to 24 year old changes significance. The rest of the coefficients remain the same sign and significance. In Model 2, the presence of white households, and age groups 25-34 years old and older than 65 years old, all become insignificant influences of the standard deviation of commuting time when we correct for spatial autocorrelation.

2.6 Implications for future research

Strategies for using sorting models to test the importance of household attributes and neighborhood characteristics have been focused on describing distributions of household income or housing expenditures, based on a logic that relies on households selecting communities based on the bundle of amenities each community offers. Once we expand the sorting model to allow for the relationship between the labor and housing market equilibriums it isn't clear that a structural sorting model can deal with a polycentric city, associating the attributes of each employment center with each community. This research investigates whether the properties of the equilibrium can be used with other outcomes of this sorting within a reduced form framework. The outcome of particular interest here is the distribution of commuting times across neighborhoods.

The results from the past literature were unable to provide conclusive evidence of the determinants of commuting time. This could be partially attributed to the level of

aggregation in the unit of analysis as well as the separate treatment of neighborhood and household characteristics as determinants of commuting time. This research suggests that by considering a unit of analysis that closely resembles a cluster of small neighborhoods, there is clear evidence that commuting time is a function of both the attributes of a household as well as the attributes of the neighborhood. Specifically, circumstances that are expected to constrain a household's flexibility appear to be important influences in commuting time.

This analysis was limited to the trip to work. Households when selecting a home also consider the accessibility that the community provides to non-work destinations. It is hypothesized that household constraints will influence the timing of non-work activities as well as the ability to minimize making trips during congested periods. The sorting model becomes more complex with these additional considerations. If it were possible to include the attributes of the locations of these non-work activities, we would again expect to find outcomes describing the distribution of travel times to non-work activities. However, data describing non-work activities are generally collected at the household or individual level. Thus, a different methodology to determine the influences of household circumstances on non-work travel patterns might be more appropriate.

The next step in the analysis would be to introduce an analytical model that allows a description of the sorting of households by commuting time as a function of heterogeneous household preferences. The estimator would move away from the current methodology of separately testing the influences of household circumstances on the moments of the commuting time distribution. Instead, we would implement a maximum

likelihood estimator that would simultaneously estimate the mean and standard deviation of commuting time as a function of the same independent variables used in this study.

Chapter Three

3.1 Introduction

Most of the literature describing households' locational choices considers local public goods, such as primary and secondary education, environmental amenities, and safety, along with the neighborhood and structural characteristics of homes as the important determinants of these choices. Some authors have followed the Rosen (1979) and Roback (1982) proposals and attempted to integrate housing and job locations into a single decision framework. None of these extensions recognize a more general consideration in locational choice – accessibility. Given a household's demographic makeup – dual earner status, number and ages of children, etc., it is reasonable to expect that there is a mix of trips expected to be a part of their activities of daily living. Trips to work are important in that mix of travel related activities. However, for many households there are other trips that can be at least as important. The costs of completing these activities are influenced by the accessibility of each residential location. This paper evaluates whether accessibility is an important determinant of households' housing choices.

This research uses a hedonic price framework to examine the impact of traffic congestion. Congestion is measured around the location of each house rather than exclusively along work/residential corridors. Congestion is defined in three different ways to determine if the estimated disamenity impact is sensitive to the implicit assumptions made in defining each index. Overall, the hedonic results for residential housing in Wake County, NC imply that the marginal price of an increase in commuting

time is capitalized into home values with an extra minute of driving leading to a \$74.37 decrease in annualized housing values. When congestion is measured as a count of vehicles on the road, annual housing values would decrease by \$2.89 for every additional vehicle on the road. After converting this measure to the congestion time effect implies a range of costs that are generally larger than \$74.37 per minute.⁴² These findings are consistent with interpreting the negative role for congestion as a reflection of the household's mix of trips rather than simply the accessibility to the workplace. The effects of congestion measured as a vehicle count includes the effect of congestion on the expected commuting time to work in addition to the effect of congestion on the other trips a household expects to make. Detecting these effects requires spatial analysis that links the measures of congestion and roadway measures to individual houses. There are also good reasons to expect that the role of congestion is endogenously determined along with prices through the choice process and that spatial autocorrelation is present in estimating the hedonic price function.

Section 2 begins with a short description of the study area and then outlines a simple model of residential choice. This framework demonstrates how choices balance multiple travel related responsibilities (e.g. trips to work as well as other types of trips) with the housing attributes and site amenities at a location. Past research has focused on the impact of work trips on housing values. This focus is important because the majority

⁴² Using the 1992 average mortgage rate for a 30-year mortgage, 8.51%. Housing values could decrease by as little as \$93.66 per year or as much as \$118.44 per year given the range of mortgage rates during the time period of this data.

of daily trips members of each household make are for non-work purposes such as eating out, child-care services and shopping.⁴³

Section 3 summarizes current literature relating traffic congestion and property values. Section 4 describes the data used and the implementation of the spatial two stage least squares estimator. Empirical results and sensitivity analyses are described in Section 5. Section 6 concludes by comparing the results from this research with the previous literature.

3.2 Modeling Residential Choice and Effects of Accessibility

A. Background

The study location for this research is Wake County in North Carolina. It includes the state capital and a large fraction of the Research Triangle Park. According to a recent study by the Center for Urban and Metropolitan Policy at the Brookings Institution, North Carolina is facing some of the most severe problems arising from rapid growth. The report notes that:

The State of North Carolina was ranked 5th among the states in the number of acres developed between 1992 and 1997. Over this five-year period, a total of 781,500 acres of land, or roughly 156,000 acres per year, were developed in the state – which means that every year, an area just larger than the city of Charlotte was developed. The pace of development appears to be speeding up. From 1982 to 1992, an average of 93,580 acres was developed each year.⁴⁴

When an area, such as the Research Triangle Park, experiences a large increase in population over a relatively short period of time, the infrastructure may be unable to

⁴³ The Final Report for the Triangle Travel Behavior Survey, Triangle Transit Authority, 1994.

⁴⁴ Adding It Up: Growth Trends and Policies in North Carolina, 2000.

provide comparable services over time. Households' choices will reflect the lack of infrastructure in some areas and the effects that these shortcomings have on the time required to travel to work and for travel related to other local services necessary for the completion of household activities. To model the role of these impacts on households' residential choices one must introduce travel as a part of household production activities. The primary framework used to integrate housing and job choice stems from the work of Rosen (1979) and Roback (1982).

The Rosen-Roback model for residential choice describes household choice focusing on the interrelationship between the housing and labor markets equilibrium. In their framework a household never changes its residential location without changing jobs. As a result the conditions for equilibrium in each market are linked. This approach has seen several applications in the literature (Blomquist et al. (1988) and So et al. (2001)). This model extends their logic by describing the role of additional travel related activities and relating them to housing choice.

Household decisions are described here within a Becker (1965) household production framework to highlight the role of time as well as money in allocation decisions. Accessibility is defined using anticipated trip taking behavior over a specified time horizon. Locations are bundled with expectations about the household members' daily activities.

Table 3.1 illustrates the potential importance of other trips using the Travel Behavior Survey for Wake County, NC to characterize the top five travel related trips listed in 1994. The sum of non work trips taken by individuals in a specified time period for this

sample is nearly three times the work trips. The number of trips taken for shopping purposes alone exceeds work trips.⁴⁵

Table 3.1 The most frequent named activities⁴⁶

Activity	Percentage
Home	21.7%
Amusement	19.8%
Work	17.5%
Meals	11.5%
Picking up/Dropping off	7.3%

B. Model

To develop the logic for the hedonic model, consider a modification of Becker's (1965) early model describing the allocation of time. Equation (3.1) provides a general specification of the preference function.

$$(3.1) \quad U(z_k, h(r, y), c, T_l)$$

where:

$$(3.2) \quad z_k = f_k(S_k, T_k),$$

z_k is the output of a household's k^{th} activity combining time and market goods to produce final consumption service flows. S_k is an $m \times 1$ vector of market goods and services, and T_k is a $q \times 1$ vector of time inputs used in producing the k^{th} commodity. Each element in S_k , s_{jk} relates to a specific market good. Each dimension of T_k refers to a different aspect of time, i.e. differentiating time used on the weekend from time used during the week.

$h(r, y)$ describes housing quality as a function of property specific attributes, r , and neighborhood attributes, y .

c is a measure of congestion

⁴⁵ Amusements include any type of entertainment including shopping.

⁴⁶ The Final Report for the Triangle Behavior Survey, Triangle Transit Authority, 1994.

T_l is the leisure time available.

Households produce final consumption flows that are combined with housing and leisure to contribute to overall well-being. By allowing congestion to enter directly into the utility function the effects of congestion are not limited to the “noise” surrounding a home.⁴⁷ Congestion may also cause direct disutility by creating stressful driving conditions during congested periods and it can influence the time required to complete activities. Congestion, as well as other housing attributes, is assumed to be selected by a household selecting a home.

The budget constraint is given in equation (3.3).

$$(3.3) \quad wT_w = \sum_m \sum_k p_m a_{mk} z_k + p_h$$

w represents the hourly wage and T_w is the number of hours worked. a_{mk} is an element of A , an $m \times k$ matrix of input requirement coefficients. Each element denotes the quantity of the m^{th} good used as an input in the production of the k^{th} commodity, such that $s_{mk} \equiv a_{mk} z_k$.⁴⁸ p_m is the price of the m^{th} intermediate good and p_h is the annual price of housing such that:

$$(3.4) \quad p_{h_j} = p_h(r_j, y_j, c_j),$$

⁴⁷ “Noise” in this instance refers to the added pollution and noise and the diminished aesthetic qualities resulting from increased congestion in close proximity to a residential location.

⁴⁸ Let a_{mk} denote the quantity of the m^{th} good used as an input in the production of the k^{th} commodity and let $A_k = (a_{1k}, \dots, a_{mk})$. The production function is denoted as: $z_k = f^k(a_{1k}, \dots, a_{mk})$ and constant returns to scale implies that $1 = f\left(\frac{a_{1k}}{z_k}, \dots, \frac{a_{mk}}{z_k}\right)$.

This relationship assumes that the individual faces the price schedule implied by a market equilibrium. The price of the j^{th} residential unit is a function of r_j , y_j and the congestion measure, c_j . The subscript j on the housing attributes will be dropped for notational simplicity.

Utility maximizing choices are constrained by the household production function (3.2), the budget constraint (3.3) and the time requirements for household activities:

$$(3.5) \quad \sum_q \sum_k t_{qk} z_k = T - T_w - T_l - \gamma(c)$$

where T represents the total time available to the household and $\gamma(c)$ represents a commuting cost function such that $\frac{\partial \gamma(c)}{\partial c} > 0$. t_{qk} is an input requirement dictating the amount of time input q required to produce z_k . Furthermore, t_{qk} is also a function of congestion and it will be assumed that $\frac{\partial t_{qk}(c)}{\partial c} > 0$ for all final service flows, $k \in K$. As congestion increases it will require more time to complete the production of a unit of z_k .

Equations (3.3) and (3.5) reduce to a single budget constraint (3.6):

$$(3.6) \quad w(T - \sum_q \sum_k t_{qk}(c) z_k - T_l - \gamma(c)) = \sum_m \sum_k p_m a_{mk} z_k + p_h.$$

Households maximize utility, equation (3.1), with respect to z, c , and T_l , subject to (3.6).

This maximization process results in the following first order conditions:

$$(3.7) \quad u_z - \lambda(w \sum_q \sum_k t_{qk}(c) - \sum_m \sum_k p_m a_{mk}) = 0$$

$$(3.8) \quad u_c - \lambda \frac{\partial p_h}{\partial c} - \lambda w \left(\sum_q \sum_k \frac{\partial t_{qk}}{\partial c} z_k \right) - \lambda w \gamma'(c) = 0$$

$$(3.9) \quad u_{T_l} - \lambda w = 0$$

$$(3.10) \quad \frac{u_c}{u_{T_l}} = \frac{\partial p_h}{\partial c} + \sum_q \sum_k \frac{\partial t_{qk}}{\partial c} z_k + \gamma'(c) w$$

Equation (3.11) provides a relationship between the marginal rate of substitution and the hedonic price function.

$$(3.11) \quad \frac{\partial p_h}{\partial c} = w \frac{u_c}{u_{T_l}} - w \left(\sum_q \sum_k \frac{\partial t_{qk}}{\partial c} z_k \right) - \gamma' w$$

(-) (+) (+)

The marginal price of congestion is isolated through a hedonic price function,

$\frac{\partial p_h}{\partial c}$. This is the result of the market equilibrium and as such will reflect both the demand

and supply sides of the market. Thus it is influenced by the preference and household production related responses of all the households in the market to congestion. Equation (3.11) suggests the marginal rate of substitution between congestion and leisure as well as the other types of adjustments a household can make in response to congestion will influence how it adapts to this marginal price. These other adjustments include how congestion impacts the production of the goods and services that the household produces. These are represented in the model through the z_k 's. The last term reflects congestion's effect on commuting time. All of these other effects are monetized by the wage which represents the opportunity cost of time in this model. With the expectation that the signs

of these three terms are as described below equation (3.11), we expect that if the equilibrium is consistent with these preference related factors then $\frac{\partial p_h}{\partial c} < 0$.

A hedonic analysis measures the marginal price of congestion. Joint estimation would be required to differentiate between the pure preference effects the household production factors and the role of supply side influences that are reflected in the effects of an adjustment in the housing market.

Hypotheses

The empirical analysis in this research addresses two questions. First can residential property value models capture spatial delineated congestion effects that are estimated to reflect generalized accessibility? Second, are property value effects sensitive to the methods used to measure congestion? Congestion is described in three ways. Each measure is related to how congestion affects the number of trips taken or to the time required to take these trips.

The first congestion measure is a spatially delineated vehicle count normalized by the width of the road. Once a road reaches near capacity, additional vehicles contribute to increased congestion. That is, an increase in the number of vehicles acts a proxy for an increase in travel time required to complete a trip. This vehicle count is thought to be the congestion a household faces while making all types of trips.

Congestion is also measured as the average reported household commuting time at the census tract level. It is recognized that this available measure of commuting time is a function of distance which depends on sprawl. However, it is also expected that

congestion may influence commuting time. To measure congestion accurately, some baseline measure of commuting time under traffic conditions at or below the “ideal” capacity of the roadways would be required. Congestion, or excess commuting time, is the difference between the reported commuting time and this baseline measure (t_b). The disparity between these two measures is likely a function of household characteristics plus an error. These characteristics determine the household’s scheduling flexibility enabling them to depart for work during non-congested periods. These household factors are unobservable in this hedonic equilibrium study, so they are likely part of the error.

$$\text{Congestion} = \text{reported commuting time} - t_b \Rightarrow \text{Reported Commuting time} = t_b + \text{error}$$

Finally both of the previous measures assume households make marginal tradeoffs in evaluating congestion. Households may not be able to gauge the actual number of vehicles on the road, but may be able to classify congested roads into groups. This formulation does not require marginal adjustments in housing prices in response to the continuous measure of congestion. Rather it suggests that market participants classify congested and non-congested areas and respond to them. Congestion, in this instance, is measured as five increasing intervals of congestion, measured as physical counts of cars normalized by the same measure of road capacity utilized in the definition of the first measure of congestion.

3.3 The Confusion in the Congestion Literature

While the prospect of using housing prices to capture congestion as a locational amenity is not new, there appear to be only four studies to date that test hypotheses concerning the

capitalization of traffic congestion into house prices. Each of these papers attempts to measure the household's response to congestion. However two important components were omitted from each of the studies. The first component suggests that ordinary least squares estimates may be biased because the correlation between the error term and the congestion variable was neglected. When a household purchases a home in relation to the workplace and other non-work related activities it is simultaneously choosing the commute and the corresponding traffic faced in completing the trip to work. One single additional vehicle is unlikely to create or increase congestion. However, similar demographic groups commonly move into the same areas and within these groups the mixes of trips households take should be similar.⁴⁹ Therefore, it is not the effect of one additional vehicle on the road but all of the additional vehicles on the road within that group that create congestion. In addition, a supply side response suggests that housing developments attract a group of similar homeowners in new neighborhoods by building homes that will attract a particular type of household. This set of new homeowners should have similar travel patterns and therefore could impact the level of congestion near the home. Secondly, in all of the papers there was no recognition of the potential for spatial correlation among the errors due to subdivision or neighborhood effects.

There is one final explanation for an endogenous congestion variable. When congestion is measured as commuting time, this variable is capturing the time it takes to drive to the workplace in the absence of congestion in addition to any extra travel time required due to congested roads. This extra travel time is likely a function of unobservable household circumstances and thus, these unobservable characteristics are

⁴⁹ This follows the rationale found in the Brock and Durlauf (2001) social interactions literature.

part of the error. Commuting time is the result of the joint choice of housing and employment locations. The value of a house is likely to be correlated with unobserved household and neighborhood attributes. Thus, it is possible that this congestion measure is correlated with the error.

Table 3.2 summarizes the four studies and highlights the inconsistencies in the results across the four studies. Hughes and Sirmans (1992) use an actual measure of traffic in close proximity to residential location. They test two models: the first relies on an actual traffic count as an indicator for congestion. The second tests the sign and significance of a high/low traffic dummy variable that replaced the actual traffic count.⁵⁰ The results provide evidence that high levels of traffic have a significant negative impact on property values. A vehicle count as a gauge of congestion may be misleading because there is no reflection of road capacity.

Guild, Schwann, and Whitehead (1998) recognize that there are several components to the cost of transport, including trip distance, traffic volume, and the value of commuting time. Two hypotheses are tested. The first is that housing prices should be higher for properties closer to frequent travel destinations because this reflects increased accessibility. To measure this effect, the authors use the distance traveled by an individual from home to the central business district. The second hypothesis suggests that worsening congestion puts downward pressure on nearby property values.

⁵⁰ Low traffic streets were defined as having only one outlet and high traffic streets were defined as thru streets.

Table 3.2 A summary of the reviewed literature⁵¹

Authors	Congestion Variable	Congestion Coefficient	Interpretation	Consistency with Accessibility Hypothesis
Hughes and Sirman (1992)	Vehicle Count	-0.0771 (sig 5%)	7.7 % decrease in housing values for each additional car	Yes
	Dummy Variable	-.0848 (sig 5%)	8.82% decrease in housing values for high traffic properties ⁵²	Yes
Guild, Schwann and Whitehead (1998) ⁵³	Change in Traffic Volume	2.131 (not sig)	2.13% increase in housing values when traffic volumes increase by 1%	No
Bateman et al (2001)	Commute Time	0.078 (sig 5%)	For every additional minute added to the commute housing values increase by 7.8%	No ⁵⁴
Tse and Chan (2003)	Commute Cost	-92.56 (sig 5%)	A dollar reduction in the commuting cost would raise the property price by \$11.96/square foot ^{55,56}	Yes
	Commute Time (linear) Commute Time (negative square)	18.29 (sig 10%) -0.219 (sig 5%)	A one minute reduction in the commuting time would raise property prices by \$2.13/square foot ⁵⁷	Only when non-monotonicity was assumed ⁵⁸

⁵¹ The significance of the estimate is reported below the estimate.

⁵² Kennedy's (1981) interpretation of dummy variables in semi-logarithmic equations was used to determine the percent decrease in housing values.

⁵³ Four different locations were tested however the coefficient listed in this table was the only significant one. Of the remaining three, two were insignificantly negative and one was insignificantly positive.

⁵⁴ This result is consistent with the authors' hypothesis but contradicts the hypothesis of this study.

⁵⁵ This study was completed in Hong Kong. The estimates are in Hong Kong Dollars but to compare results across the studies the interpretation of the results have been converted from Hong Kong Dollars to U.S. Dollars.

⁵⁶ The authors reported that the average apartment in Hong Kong was 600 square feet implying that property prices would go up by \$7,177 on average for the dollar reduction in the commuting cost.

⁵⁷ For the average 600 square foot house, property values would increase by \$1278.

⁵⁸ This result only holds when the commute time changes from 80 minutes to 79 minutes. If the commute time is originally 40 minutes then additional commute time actually increases property prices.

To test this hypothesis, the change in traffic volume over time is used as a proxy for worsened congestion. Their findings largely contradict their expectations; properties further away from the central business district were more valuable than were closer properties, rejecting their first hypothesis. In addition, property prices in this study area do not respond to worsening congestion.⁵⁹

Bateman et al (2001) test the effects of traffic congestion on housing values in Glasgow to determine the compensation that households would receive as a result from the noise, vibration, smell, fumes, smoke, artificial lighting and discharge onto the land of solid and liquid substances.⁶⁰ Many variables are used to represent a measure of the property's exterior structural qualities. The primary focus of the paper is on the effects of specific variables considered as proxies for accessibility. These variables are defined as the ease with which local amenities could be reached from each property. Three separate accessibility measures are used: car travel time, walking distance, and straight-line distance. The coefficient on the car travel time variable to the city center, rail station and nearest local show are all positive, implying that property prices are higher for a house further away from the city than to a similar house closer to the city. The authors also find that at some point driving too long would be a disamenity.⁶¹

⁵⁹ The study area is Auckland, New Zealand, regarded as a monocentric city but is recently following the trend of urban sprawl that is prevalent in the United States.

⁶⁰ As a response to the Land Compensation Act of 1973 in England, the legal owners of residences can be compensated for the reduction of value in their land resulting from the construction and presence of public works.

⁶¹ This was captured with squared travel times.

Tse and Chan (2003) estimate the effects of both commuting cost and commuting time on apartment sales prices in Hong Kong.⁶² They impute both the monetary and time costs of commuting by using the fares and schedules from the public transportation system from each location to the central business district. In total three variables are used as determinants of apartment prices: the year the apartment building was built, commuting time and commuting cost. The results suggest that an increase in monetary commuting costs would put downward pressure on apartment prices. The authors further assume that the relationship between commuting time and apartment prices is non-monotonic. As a result commuting times have a negative effect on apartment prices but, this result only holds for commuting times over 40 minutes.

This research addresses the shortcomings raised in this review by modeling the impact of congestion on the set of typical trips a household makes. In addition, the estimation considers the nature of the spatial data and the jointness in housing location, workplace, and the commute to and from both of these places.

3.4 Data

The data used for this research are derived from four different sources. The first is parcel data for homes sold in Wake County, North Carolina. The data, purchased from a commercial vendor, Trans America Intellitech, consisted of single-family owned residences that had been sold between 1992 and 1999. These data were previously merged with Wake County parcel records giving specific housing attributes. In addition

⁶² The authors use the average apartment sales price within each apartment building as the dependent variable because they did not have any information on apartment specific characteristics.

each parcel is geo-coded and contains information on the census tract, a collection of housing attributes such as area, the number of bathrooms, the year of sale, and a large number of dummy variables identifying the presence of a fireplace, garage, etc., and sales prices.

The second data set describes structural properties of all roads in Wake County. North Carolina Department of Transportation (NC DOT) collected data by sections of the road and listed this information by the route number or street name as well as the road's functional classification, such as interstate, expressway, local or rural. Relevant variables include the surface type of the road, the width of the road, and any type and year of improvement that was made for that particular section of the road. In addition, the speed limit on that road and the percentage of trucks that used that road both during peak time and off-peak time are also included. There are a total of 5,702 observations, where the unit of observation is a section of a road. The third data set was also collected by the NC DOT. These data provide the average annualized daily traffic count for 5,400 different traffic count stations in Wake County. The data were collected every other year from 1990 until 1998. In addition, each traffic count station was geo-coded.

The final data set was gathered using the U.S. Census. Data were collected for all census tracts in Wake County for the completed Census of 2000. The variables selected provide information on demographic variables such as race, age, and income. In addition there are two traffic variables included: the method of traveling to work (i.e. car, bus, and carpool) and the amount of time spent commuting to work.

These four data sets are merged in three steps. The first step links the structural properties of the roads to a traffic count station by a unique identification number that

was present in both data sets. A relative congestion measure was constructed using the vehicle count number and scaled by the reciprocal of the surface width of that road.⁶³ The second step links each residential property with a congestion measure by locating the nearest traffic count station based on the shortest straight line distance from the property to one of the 5,400 traffic count stations. The traffic from the year prior to the sale was used to measure the count of vehicles relevant to each house.

Finally the census tract number was used to combine the census tract data with the rest of the aforementioned database. The final data set includes 39,154 observations. Table 3.3 summarizes the attributes of the data, the level of spatial resolution and the method used to link the data.

Table 3.3 Merging methodology used in the culmination of the final database

	Data Set One	Data Set Two	Methodology Used in Merging	Result
Step One	Physical properties of roads	Geo-coded traffic count stations	Unique identification number present in both data sets	Total NC DOT data Traffic counts and corresponding structural road properties (5,400 count stations)
Step Two	Total NC DOT data (geo-coded)	Wake County parcels and attributes (geo-coded)	Nearest straight line distance from property to traffic count station	Parcels with housing attributes and congestion and road properties (39,154 properties)
Step three	Data resulting from step two	U.S. Census Wake County neighborhood and commuting time variables	Census Tract information was included in both data sets	Final data set; Geo-coded parcels with congestion and road properties and census level neighborhood variables (39,154 properties)

⁶³ This measure of congestion would be the number of cars relative to the number of lanes on the road. However, the lane data was incomplete. Thus, the surface width of the road acted as a proxy for capacity for each observation.

A map of Wake County is shown in Figure 3.1 with some of the larger cities represented. In addition, some of the major highway arteries are shown. There is one interstate highway, I-40 that begins on the coast of North Carolina. There are also two large freeways: the Beltline, I - 440, that circles the city of Raleigh and I – 540, a new partially completed highway that provides a direct route from North Raleigh to the Research Triangle Park.

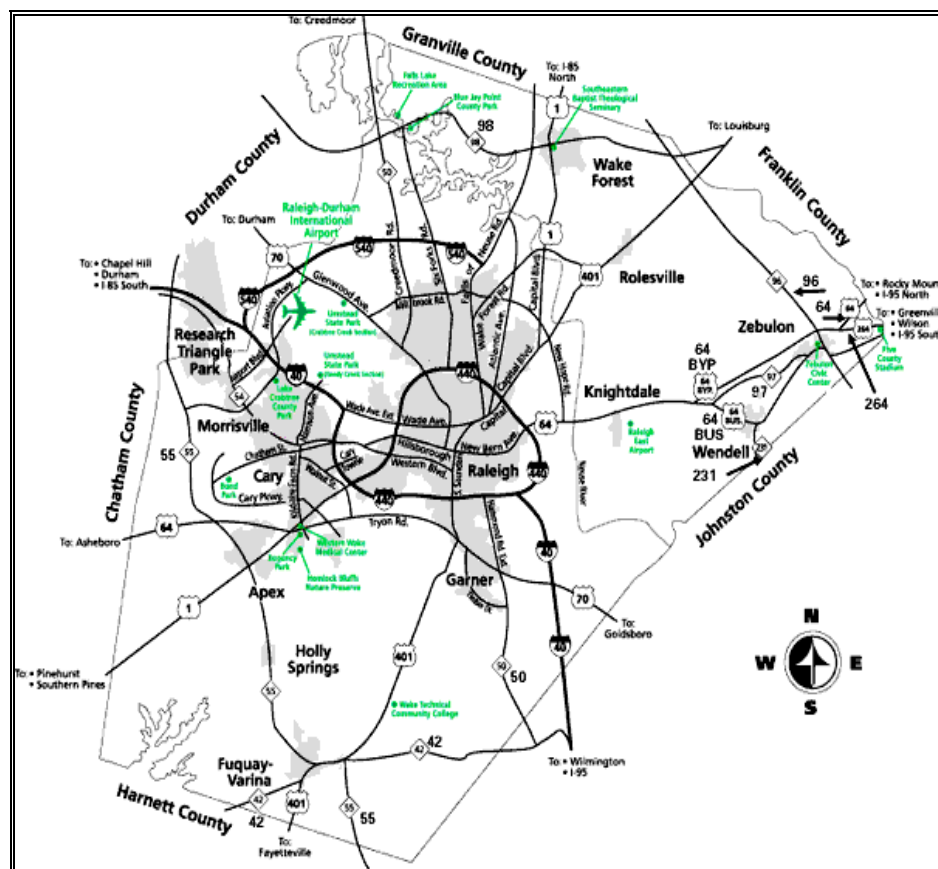


Figure 3.1 Wake County City and Road Map

Table 3.4 and Table 3.5 provide an overview of the housing variables and road characteristic variables, summarized by some of the larger municipalities in Wake County to display the differences across the eastern and western parts of the county.

Table 3.4 Selected Wake County housing attribute means

	Raleigh	Knightdale	Holly Springs	Garner	Cary	Apex
House price	\$146,785	\$109,227	\$168,888	\$109,834	\$189,243	\$182,643
Number of bathrooms	2.43	2.19	2.52	2.01	2.76	2.73
Stories	1.54	1.32	1.61	1.32	1.67	1.68
Rooms	5.71	4.89	4.82	5.45	6.36	5.12
Square area of house	1,841.71	1,443.46	1,940.88	1,575.67	2,253.17	2,206.69
Year house was built	1981	1987	1994	1981	1987	1992
Year house was sold	1995	1995	1996	1995	1995	1996
Travel time to work household (mins)	29.1	35.1	35.5	32.3	29.3	31.4
Travel time to work individual (mins)	11.7	12.8	12.5	12.2	10.9	11.3
Percentage white in census tract	82.07%	83.92%	37.30%	78.56%	86.39%	82.51%
Speed (MPH)	44	43	48	41	42	44
Miles from home to RTP	16.47	25.23	19.94	23.13	12.36	11.90
Miles from home to downtown Raleigh	6.73	10.17	15.65	7.13	9.81	13.51

Table 3.5 Road characteristic statistics by city in Wake County, NC

	Raleigh	Knightdale	Holly Springs	Garner	Cary	Apex
Miles from home to RTP	16.47	25.23	19.94	23.13	12.36	11.90
Miles from home to downtown Raleigh	6.73	10.17	15.65	7.13	9.81	13.51
Travel time to work household (mins)	29.1	35.1	35.5	32.3	29.3	31.4
Travel time to work individual (mins)	11.7	12.8	12.5	12.2	10.9	11.3
Average daily traffic count (#cars)	18,028	7,988	3,680	9,756	14,619	6,575
% increase in traffic from 1991 to 1998	27%	17%	82%	11%	44%	71%
Speed	44	43	48	41	42	44
Surface width (feet)	40.4	21.2	21.8	30.8	35	30
Year of last improvement	1978	1983	1986	1988	1985	1989

To ensure that the process of linking a property to the nearest traffic count station is comparable across jurisdictions, Table 3.6 presents the average distances between

traffic count stations and properties for houses in each city. In most instances, the average house is about one half of a mile away from the closet traffic count station, and no house in the six cities listed is located more than two miles away.

Table 3.6 Distance from property to nearest traffic count station (feet)

	Mean	Std Deviation	Minimum	Maximum
Raleigh	2284	1300.2	8.56	7364
Knightdale	3097	1468.7	20.2	10516
Holly Springs	2825	1601.7	44.0	6809
Garner	2007	1271.7	44.5	5654
Cary	2054	1029.2	22.8	5881
Apex	2184	880.7	46.7	5717

Implementation

The empirical analysis recognizes the potential effects of spatial autocorrelation and endogeneity in the congestion measure. These issues are discussed separately. However final estimates evaluating the effects of congestion reflect consistent adjustments that account for the presence of both spatial autocorrelation and endogeneity of the congestion variable.

The first step of the analysis requires the selection of a functional form for the hedonic price function.⁶⁴ Equation (3.12) illustrates the components of the price function using a semi-log functional form:

$$(3.12) \quad \ln p_{hj} = \alpha_j^{SL} r_j + \mu_j^{SL} y_j + \gamma_j^{SL} fe_j + \eta_j^{SL} c_i + \varepsilon_j^{SL} .$$

⁶⁴ Three separate functional forms were investigated: linear, semi-log, and a linear Box-Cox transformation. Cropper, Deck and McConnell (1988) found that when the price function in a hedonic model could be assumed to include all of the relevant attributes, then the linear and quadratic Box-Cox specifications resulted in the best estimates, whereas if there were some attributes that were unobserved, linear and linear Box-Cox forms provided the best estimates. In addition they found that the semi-log function produced errors with a narrow spread.

Each term in (3.12) is a vector reflecting a class of variables. For example, the r_j 's include the characteristics of each house and its lot, the y_j 's are the variables representing the neighborhood characteristics, the fe_j 's are the fixed effects, and c_j 's are the variables representing traffic congestion measures.⁶⁵ The ε_j 's represent the unobservable characteristics of the house.

Both the semi-log and the Box Cox specifications produced estimated coefficients consistent with a priori expectations.⁶⁶ The estimates and corresponding standard errors across the two functional forms were similar and Box Cox parameter, λ , was not significantly different from zero.⁶⁷

Congestion: An Endogenous Variable

There are a number of reasons to hypothesize that similar types of households will be attracted to each location. With some lag, it also seems reasonable to expect supply responses to these households' choices. The available congestion measures reflect composite outcomes of these processes at a specific time. Thus, we might expect the congestion measures to be endogenous. To adjust for this endogeneity requires forming instruments for the congestion measure. Three instruments were selected from the NC

⁶⁵ Fixed effects in this case are dummy variables used to represent the year of sale.

⁶⁶ The linear model produced estimates that rejected some of the hypotheses that are standard in most housing price models. The coefficients on variables such as bathrooms and age were either insignificant or of the unexpected sign.

⁶⁷ While using a semi-log specification may result in a functional form that is not perfectly specified, the Box-Cox would make spatial autocorrelation and endogeneity adjustments much more difficult. Therefore the semi-log specification was retained to allow for the estimation of these additional considerations.

DOT structural road properties: the percentage of trucks on the road during peak time, the road surface type, and the speed limit on the section of road that is observed at the closest traffic station in closest proximity to the house. All three variables display high correlation with the congestion variable and low correlation with the errors.⁶⁸

Spatial Autocorrelation

Locational choice within a spatially delineated road network, a given set of employment opportunities, and amenities create the prospect of a spatial dependence between the resulting equilibrium housing prices and thus the errors in a hedonic model. Spatial dependence refers to the fact that one sale price in a location may well depend on other observations at other neighboring locations as shown in equation. Corrections for spatial autocorrelation generally represent the interdependency using a generalized form of a spatial correlation. The process is described as a spatial autoregressive process for the error.

To outline the process consider a more general statement of the hedonic model first present in equation (3.12) by adding structure to the error term:

$$(3.13) \quad P_h = X\beta + \varepsilon \quad \text{where} \quad \varepsilon = \rho W\varepsilon + u$$

⁶⁸ The table below provides one way to gauge of the quality of the instruments – single correlation with the congestion measure and correlation with the OLS residuals from the model.

Instrument	Correlation with vehicle count (correlation with residuals second column)		Correlation with commuting time (correlation with residuals second column)	
% trucks in peak period	0.5388	0.0230	0.8550	0.0159
Surface type	0.4021	-0.0211	0.5433	-0.0104
Speed limit	0.6462	0.0141	0.6440	0.0083

where P_h is an $n \times 1$ vector of observations on the dependent variable, X is an $n \times k$ matrix of explanatory variables, β is a corresponding vector of unknown parameters, W is an $n \times n$ spatial weight matrix, ρ is a scalar parameter to be estimated, u is an $n \times 1$ vector of random error terms with expected value of 0 and variance-covariance terms matrix $\sigma^2 I$.

Solving for ε in the second part of (3.13) and substituting into the first part of (3.13) we have:

$$(3.14) \quad P_h = X\beta + (I - \rho W)^{-1}u$$

The Weighting Matrix

The spatial weight matrix, W , contains information describing the assumed spatial relationship between each pair of errors. The i^{th} , j^{th} element of W , denoted w_{ij} , represents the potential spatial dependence between the i^{th} and j^{th} error term, where $w_{ii} = 0$ for $i = j$. Two different types of spatial weighting matrices are considered. The first is the first-order contiguity matrix. In this framework the elements of space $W=1$ if the distance between two parcels is less than some predetermined cutoff distance, b . This matrix is synonymous to the nearest neighbor matrix where each neighbor receives the same weight regardless of how the neighbors are distributed provided the neighbor falls within the cutoff distance. The matrix is row standardized so that the elements in each of the rows of the matrix sum to one.

The second weighting matrix considered was the inverse weighting matrix. In this formulation the elements of W are defined as $w_{ij} = 1/d_{ij}$ if $d_{ij} < b$ where d_{ij} is the distance between two observations, i and j , and $w_{ij} = 0$ if $i = j$ or if $d_{ij} > b$. The larger the cutoff distance, the less sparse is the weighting matrix. This weighting matrix was also row-standardized. For both types of matrices, two different cutoff distances were used, 200 meters and 400 meters.⁶⁹

Estimation of the Autocorrelation Parameter

When error terms are spatially correlated, ordinary least squares produces inefficient parameter estimates and biased estimates of standard errors. As a rule, the parameters (β, ρ, σ^2) are estimated by maximizing the log-likelihood function:

$$(3.15) \quad \ln L = \ln \|I - \rho W\| - \frac{N}{2} \ln(2\pi) - \frac{N}{2} \ln(\sigma^2) - \frac{(y - \rho W y - X\beta + \rho W X\beta)^T (y - \rho W y - X\beta + \rho W X\beta)}{2\sigma^2}$$

Feasible generalized least-squares estimates of β and σ^2 are calculated using $\hat{\rho}$, an estimate for ρ . To complete this estimation the eigenvalues of the spatial weighting matrix, W , need to be calculated. This process requires the computation of the inverse of W . For small data sets, this task would not raise difficulties, but for large sample sizes computing this inverse to measure the eigenvalues becomes very computationally cumbersome. Moreover the precision of the estimation decreases as the size of W increases. As a result an alternative strategy was adopted.

⁶⁹ These cutoff distances are chosen for two reasons. Previous literature (Bell and Bockstael, (2000) used these cutoff distances. In addition, the distribution of houses in the area resulted in a weighting matrix that was too dense after 400 meters. At 200 meters, it ensured that a large portion of the houses had at least one neighbor.

When sample sizes are large, a generalized-moments estimator (GME, Kelejian and Prucha, (1999)) is more tractable. The GME approach doesn't require the calculation of eigenvalues, only the trace of the weighting matrix. Using GME, a consistent estimate of ρ can be obtained yielding consistent and asymptotically efficient estimates of β and σ parameters. ρ is estimated by minimizing the three moment conditions of the error term (as detailed in Appendix C) and generalized least squares (GLS) was used to estimate the parameters, β along with σ^2 .⁷⁰

Combining the Spatial Parameter with the Endogenous Congestion Variable

To recover the final estimates that incorporate both the spatial autocorrelation parameter and congestion entering as an endogenous variable, a three-step procedure is used that is similar to the method developed by Kelejian and Prucha (1998). However, in this application a spatially lagged dependent variable is replaced with an endogenous variable, congestion.

The first step of the estimation is to compute the 2SLS with the instruments previously discussed.

$$(3.16) \quad \tilde{\delta}_n = (\hat{Z}_n^T \hat{Z}_n)^{-1} \hat{Z}_n^T y_n$$

where $\hat{Z}_n = H_n (H_n^T H_n)^{-1} H_n^T X_n$, and H_n are a $n \times p$ set of instruments and X_n are the $n \times k$ set of exogenous regressors with $p > k$ and y_n is the endogenous right hand side variable.⁷¹ In this instance it is the congestion measure.

⁷⁰ For the detailed discussion of the Generalized Moments Estimator see Appendix B.

⁷¹ n denotes the variable is conditional on the size of the sample.

The second step uses residuals obtained from the first step (3.16) and then computes the GME estimates for the spatial autoregressive parameter. The final step re-estimates the regression by 2SLS by transforming the model using a method described below to account for spatial autocorrelation.

This step assumes that ρ is not known but has been estimated so that $\hat{\rho}$ replaces ρ in the final estimation step. The equation for the third step coefficient $\hat{\delta}_n$ is:

$$(3.17) \quad \hat{\delta}_n = [\hat{Z}_{n*}(\hat{\rho}_n)^T \hat{Z}_{n*}(\hat{\rho}_n)]^{-1} \hat{Z}_{n*}(\hat{\rho}_n)^T y_{n*}(\hat{\rho}_n)$$

with $\hat{Z}_{n*}(\hat{\rho}_n) = (H_n(H_n^T H_n)^{-1} H_n^T)(X_n - \hat{\rho}_n W_n X_n)$ and $y_{n*} = y_n - \hat{\rho}_n W_n y_n$.

The asymptotic variance covariance matrix associated with $\hat{\delta}_n$ is:

$$(3.18) \quad \hat{\sigma}_{\varepsilon,n}^2 [\hat{Z}_{n*}(\hat{\rho}_n)^T \hat{Z}_{n*}(\hat{\rho}_n)]^{-1}$$

where $\hat{\sigma}_{\varepsilon,n}^2 = (\hat{\varepsilon}_n^T \hat{\varepsilon}_n) / n$ with $\hat{\varepsilon}_n = y_{n*} - (X_n - \hat{\rho}_n W_n X_n) \hat{\delta}_n$.

3.5 Estimation Results

Table 3.7 presents the estimates of the hedonic price function for a sample composed of sales from 1992 to 1999. The specification includes the vehicle count as the measure of congestion. The estimation methodology features distinguish the models reported in the table. The first column reports estimates from an ordinary least squares regression. The second column instruments for the hypothesized endogenous congestion measure and then describes the results from the two-stage least squares estimation. The third column only considers spatial autocorrelation and ignores the potential for endogeneity. Finally,

the last column simultaneously addresses both endogeneity and spatial autocorrelation. The reported estimates result from a generalized two-stage least squares procedure.

Throughout each of the four estimation strategies, nearly all of the structural attributes of a house (bathrooms, area, garage, etc) have the expected signs and are highly significant. The coefficient for the age of the house is the only exception. After correcting for endogeneity and spatial autocorrelation, age is positive and insignificant. All four of the socio-demographic neighborhood characteristics are significant. Fixed effects to reflect the sale year are included with 1992 as the normalizing year.⁷²

Other variables of interest are miles to downtown and miles to the Research Triangle Park. The miles to the Research Triangle Park coefficient was negative implying that housing was less desirable the further it was located from the Research Triangle Park. Although there are several business centers in the Wake County area, the Research Triangle Park is considered to be the largest and most prominent one. The miles to downtown coefficient is positive inferring that being close to the downtown area is a disamenity, perhaps due to parking, crime, noise, etc.

It is of special interest to note that the effects of congestion vary by the treatment of the potential for endogeneity of the congestion variable. Congestion appears to be an amenity if endogeneity is ignored, the coefficient is positive both with OLS and GLS estimation. This result is consistent with the confusion in the previous literature. Only after correcting for endogeneity do we get results that are consistent with the hypothesis that congestion is a disamenity.

⁷² The fixed effects were significant but were not reported in Table 7 to conserve space. The fixed effects coefficients can be found in Appendix D.

Table 3.7 Hedonic results, $y = \log(\text{housing prices})$, congestion = traffic count⁷³

	OLS Estimation	IV Estimation	GLS Estimation	Generalized 2SLS
Constant	11.1321 (196.20)	11.1901 (193.80)	10.9413 (182.5)	11.0752 (172.31)
Age of house	0.0117 (4.35)	0.0132 (4.85)	-0.0035 (-1.33)	0.0043 (1.56)
Baths	0.1950 (98.75)	0.1946 (97.59)	0.1753 (94.05)	0.1840 (93.72)
Fireplace	0.0007 (127.66)	0.0007 (126.45)	0.0006 (115.68)	0.0007 (40.61)
Garage	0.1456 (42.06)	0.1471 (42.02)	0.1285 (39.90)	0.13820 (49.96)
Area	0.0361 (53.87)	0.0358 (52.84)	0.0317 (49.85)	0.03340 (116.75)
Square Area	-0.0019 (-6.63)	-0.0018 (-6.40)	-0.0008 (-3.39)	-0.0013 (-5.011)
Age in census tract	-0.3032 (-5.16)	-0.2862 (-4.82)	-0.0203 (-0.33)	-0.1184 (-1.80)
Income in census tract	-0.3275 (-5.67)	-0.3115 (-5.34)	-0.0373 (-0.61)	-0.1420 (-2.19)
% white in census tract	-0.0043 (-20.4)	-0.0053 (-21.38)	-0.0066 (-22.62)	-0.0065 (-17.97)
% black in census tract	0.4728 (31.64)	0.5459 (30.95)	0.6695 (32.58)	0.6443 (25.44)
Miles to Research Triangle Park	-0.0080 (-36.67)	-0.0082 (-37.04)	-0.0088 (-28.82)	-0.0088 (-27.20)
Miles to downtown	0.0034 (10.38)	0.0013 (2.99)	0.0062 (13.98)	0.00270 (4.57)
Congestion variable	0.0002 (13.06)	-0.0002 (-4.03)	0.0002 (8.97)	-0.0002 (-2.931)

⁷³ Estimated with a 200 meter inverse distance weighting matrix. t-statistics are reported underneath the estimates.

Table 3.8 describes the results for the other two models when congestion is measured as commuting time and as increasing intervals of congestion. Only the results from the generalized two-stage least squares estimation are reported for both models because the signs of the coefficients do not change from what is originally estimated from OLS, 2SLS, and GLS.

As expected, commuting time has a negative influence on housing prices. However, when the piecewise regression was estimated, allowing for the five increasing levels of congestion, all but one of the coefficients was positive. Furthermore, only one of the coefficients was significant. The hypothesis maintained that the slope within each of the congestion intervals would be constant but would be increasingly negative after each break point. A Wald test was used to test the restrictions that the congestion coefficients of the piecewise regression are all equal to each other. The Wald test is distributed as χ^2 with 10 degrees of freedom. The test statistic was 0.2487 which falls below the critical value. This signifies that the restrictions can not be rejected conditional on the breakpoints chosen. Thus, the marginal normalized vehicle count appears to have a constant effect on housing price. Therefore, the model with congestion measured as a single variable should be used.

Using the average Wake County house price of \$154,868, an additional car on the road would decrease annual housing rents by \$2.86, while increasing the commute time by one minute would decrease annual housing rents by \$74.37. However, increasing levels of congestion have inconsistent impacts on housing rents. Only the 40% interval was significant from the estimation and the impact of congestion on annual housing rents

is actually positive. A summary of the congestion variable coefficients is given in Table 3.9.

It is possible to convert the two measures of congestion, traffic count and commuting time, into a common value to allow for a comparison between them. These measures are not expected to be equal because they measure different aspects of congestion. The commuting time variable measure is expected to measure both the impact of congestion and sprawl on the trip to work whereas the vehicle count variable seems likely to offer a measure that captures the impact of congestion on all types of trips, including work trips. The expectation is that the impact of congestion measured by increased commuting times will be smaller than the impact of congestion on all types of trips.

The literature suggests that for every additional car per mile on the road we should expect speed to decrease from 0.3mph to 4mph.⁷⁴ These measures vary with the type of road, signal lights and the prevailing speed limit on the road. It is likely that the conversion results will vary by areas within Wake County because the road networks, land use and population density change as you move away from downtown. Downtown Raleigh consists of approximately 1,378 miles of roads. On average there were an additional 794 cars every year that passed by the average residential location in Downtown Raleigh. This increase in cars would reduce speed from 0.174mph to 2.32 mph.

⁷⁴ The Center for Transportation Research and Education reports that the speed on the roadway reduces by .3mph for every additional vehicle on that road per mile of road. The reported 4mph came from an update of the Transportation Research Board (TRB) Special Report 165, "*Traffic Flow Theory*," published in 1975.

Table 3.8 Generalized two stage least squares results, $y = \log(\text{house price})$, Congestion = commuting time and increasing intervals⁷⁵

	Commuting Time	Interval Variable
Constant	10.8162 (114.73)	10.9909 (98.22)
Age of house	-0.0016 (-0.49)	-0.0045 (-0.94)
Baths	0.1784 (68.80)	0.2022 (82.02)
Fireplace	0.0007 (102.51)	0.0007 (95.89)
Garage	0.1335 (36.92)	0.0814 (3.22)
Area	0.0352 (40.89)	0.0365 (43.38)
Square Area	-0.0014 (-5.46)	-0.0013 (-4.19)
Age in census tract	-0.0027 (-2.60)	-0.0838 (-0.65)
Income in census tract	0.6664 (23.38)	0.5517 (16.54)
% white in census tract	0.1265 (1.24)	-0.0045 (-8.72)
% black in census tract	0.0672 (0.72)	-0.1221 (-0.95)
Miles to Research Triangle Park	-0.0093 (-24.04)	-0.0123 (-14.20)
Miles to downtown	0.0073 (6.34)	0.0077 (8.81)
Congestion variable	-0.0052 (-3.22)	n/a
First level congestion	n/a	-0.0010 (-0.68)
Second level congestion	n/a	0.0017 (1.97)
Third level congestion	n/a	0.0003 (0.61)
Fourth level congestion	n/a	0.0000 (0.1185)
Fifth level congestion	n/a	0.0002 (0.94)

⁷⁵ t-statistics are in parentheses below the estimates.

Table 3.9 Summary results and marginal price of congestion⁷⁶

Congestion Variable	Coefficient	Interpretation	Change in Housing Value ⁷⁷
Vehicle Count Constrained by Width of the Road	-0.0002	For every additional car on the road, annual rents would fall by 0.02%	\$ -2.86
Commute Time	-0.0052	For every additional minute added to the commute, annual rents would fall by .52%	\$ -74.37
		For increasing levels of congestion, annual rents would change by	
Lowest 20%	-0.001	-0.1%	\$-14.30
40%	0.0017	0.17%	\$ 24.31
60%	0.0003	0.03%	\$ 4.29
80%	0.0000	0.00%	\$ 0
Highest 20%	0.0002	0.02%	\$ 2.86

The average Wake County household drives 70.8 miles per day and the average posted speed limit is 43.6 mph. Therefore these additional cars would increase travel time from 0.39 minutes to 5.48 minutes. However, the roads downtown have primarily a lower posted speed limit and many traffic signals. It is then reasonable to expect that additional cars would have a greater impact on speed than you would find with cars on the interstate highways and other roads with higher speeds and fewer traffic lights. Therefore, it is expected that the change in travel time would actually be substantially

⁷⁶ The results were estimated with the inverse distance weighting matrix with a cutoff distance of 200 meters.

⁷⁷ These estimates were calculated using the average house price of \$154,868 in Wake County, and the average thirty year mortgage rate over the course of the study of 8.5%.

larger than the lower bound of 0.39 minutes and much closer to the upper bound of 5.42 minutes.

Table 3.10 reports the changes in speed limit and travel time with the given conversion rule for five sections of Wake County. In addition, the last column reports the decrease in annual housing rents for an additional minute of travel resulting from the average additional cars on the road near a residential location. This measure accounts normalizing capacity measure, the surface width of the road, by multiplying the regression coefficient by the average surface road width in the county.

In all but one of the areas, the lower bound on the \$/minute value is less than the \$/minute of commute time, \$74.37 but in all cases the upper bound is at least six times larger.⁷⁸ Western Wake County is the only area where the \$/minute is always greater than the \$/commute minute. Western Wake County is located right off of I-40 where speeds are much higher and there are no traffic signals but there are many travelers. You would expect then that the decrease in the speed on I-40 to be closer to .3mph than the upper bound. The other sections of the county consist of smaller highways and, on average, lower speeds. Therefore, additional cars would result in a larger decrease in speed.

The range for these values is very large, given the circumstances of the road networks and the assumptions made about the trip making behavior of households (i.e., the average vehicle miles traveled). Generally the marginal effect of congestion measured as a car count converted to time will be larger than the measure using commute

⁷⁸ The average increase in commute time is approximately .50 minutes per year each way for a household, resulting in an additional minute of daily commute time.

time. While this is not an exact interpretation, these results suggest that the impact of congestion on all trips is greater than the impact of simply considering the trip to work.

Table 3.10 Results from converting the \$/Car measure to \$/Minute

Wake County Subsections	Effect of Additional Cars on Speed⁷⁹	Effect on Additional Cars on Time⁸⁰	\$/Minute⁸¹
Downtown Raleigh	.17 mph 2.32 mph	.39 minutes 5.48 minutes	\$ 39.82 \$ 559.51
East Wake County (Wendell)	.14 mph 1.88 mph	.32 minutes 4.39 minutes	\$ 32.68 \$ 448.68
West Wake County (RTP, Cary)	.40 mph 5.28 mph	.89 minutes 13.43 minutes	\$ 91.28 \$1371.20
South Wake County (Garner, Holly Springs)	.19 mph 2.48 mph	.42 minutes 5.87 minutes	\$ 42.90 \$ 599.33
North Wake County (North Raleigh, Wake Forest)	.22 mph 2.92 mph	.49 minutes 7.01 minutes	\$ 50.02 \$ 715.72

Sensitivity Analysis

Bell and Bockstael (2000) found their estimates of the autocorrelation parameter and the hedonic coefficients for Maryland were more sensitive to the choice of the weighting matrix than to the estimation technique (GME or MLE). Therefore, Table 3.11 provides the results of a comparable sensitivity analysis. For each congestion variable, four sets of estimates were completed. There were two types of weighting matrices used, the inverse

⁷⁹ The small amount of transportation literature suggests that every additional car per mile will decrease speed by .3mph to 4mph. The first row of each section of Wake County represents the rule of .3mph and the second row represents the rule of 4mph.

⁸⁰ Assuming an average speed of 43.6mph and an average of 70.8 daily miles driven per household.

⁸¹ Multiplying the regression coefficient of \$2.86/(car/surface width) by average road width results in \$102.10 reduction in annual housing rents per year per additional car that drives by a residential location. This measure was multiplied by the additional time required for the average additional vehicles on the road in each section of Wake County to determine the effect of an additional car on travel time.

distance weighting matrix, and the row standardized contiguity matrix. In addition, two cutoff distances were chosen, 200 meters and 400 meters.⁸²

It appears that the results are not sensitive to the type of weighting matrix used; however, they are sensitive to the cutoff distance chosen. In all instances, the estimated spatial autocorrelation parameter falls between 0.44 and 0.65, ensuring the significance of correcting for spatial autocorrelation. While the congestion estimates always remain the same sign and significance, when the cutoff distance increases, the magnitude of the coefficient increases. For example, when an inverse distance weighting matrix with a cutoff of 400 meters is used, the coefficient on commute time changes from -0.0052 to -0.0085. For each additional minute added to the commute, this translates into a decrease in annual rents of \$121.57 for the average house in Wake County. This is significantly larger than the shorter cutoff distance result.

3.6 Conclusion

Estimation of a hedonic price equation for residential home sales, including measures for congestion, provides evidence that the market does take account of accessibility and congestion. The estimates suggest that traffic congestion measured as a vehicle count and traffic congestion measured as commuting time both had a negative effect on property prices. It is difficult to distinguish if the commuting time measure is mostly measuring sprawl or congestion. Just fewer than 60% of the houses sold during the time period of this study were built before 1990. This might suggest that while sprawl may

⁸² The full set of estimates can be found in tables D1- D3 in Appendix D.

play a role in increased commuting times, congestion may also be a factor in this particular equilibrium.

Table 3.11 Congestion parameter estimates

	Inverse Distance Weight Matrix		Row Standardized Ones Weight Matrix	
Congestion Variable	Cutoff = 200 m	Cutoff = 400m	Cutoff = 200 m	Cutoff = 400 m
<i>Model 1</i>				
Vehicle count /surface width	-0.0002 (-2.93)	-0.0002 (-2.43)	-0.0002 (-2.90)	-0.0002 (-2.43)
<i>Model 2</i>				
Commute time	-0.0052 (-3.22)	-0.0085 (-3.70)	-0.0053 (-3.24)	-0.0093 (-3.85)
<i>Model 3</i>				
1 st level	-0.001 (-0.68)	-0.0004 (-0.15)	-0.0010 (-0.65)	-0.0001 (-0.05)
2 nd level	0.0017 (1.97)	0.0023 (1.83)	0.0017 (1.95)	0.0024 (1.82)
3 rd level	0.0003 (0.61)	0.0007 (1.08)	0.0003 (0.59)	0.0008 (1.18)
4 th level	0.0000 (0.19)	0.0000 (0.06)	0.0000 (0.09)	0.0001 (-0.11)
5 th level	0.0002 (0.94)	0.0003 (1.12)	0.0002 (0.94)	0.0003 (1.17)

Online mapping services provide travel times in the absence of congestion from different areas of Wake County to the Research Triangle Park and to Downtown Raleigh, the two largest employment centers in the area (Table 3.12).⁸³ These travel times are all larger than the commuting times reported in the census (Table 3.5). Without household level commuting time data, it is not possible to compare the baseline measures reported in Table 3.12 with the reported commuting times to determine the influence of congestion on commuting time. The coefficient on the commuting time to work may not be constant

⁸³ These times were calculate from Mapquest.

across locations. There appears to be some variability in travel times by location as described in Table 3.12. This provides an additional explanation for testing for spatial autocorrelation.

Table 3.12 Baseline commuting time measures by city

Travel From	Travel time to RTP	Travel time to Downtown Raleigh
Knightdale	34 minutes	21 minutes
Cary	18 minutes	16 minutes
Holly Springs	33 minutes	27 minutes
Garner	28 minutes	11 minutes
Apex	27 minutes	21 minutes
Raleigh	24 minutes	N/A

The hedonic model does not necessarily reflect all the ways congestion can influence people's preferences. There are limits to what can be concluded about structural relationships from functions that characterize equilibrium prices. Hidano (2002) compares the effects of improvements in accessibility within a hedonic framework to the welfare benefits associated with an accessibility improvement in a structural model. While the hedonic overstates the benefits associated with the improvement, the difference between the two estimates was less than 10%. While accounting for the heterogeneity in households might enhance what can be learned from the hedonic, it is still possible to obtain an estimate of the value of different kinds of congestion.

In contrast to the mixed record of the previous congestion studies, the results from this research are consistent with the proposed hypotheses. If the endogeneity of the congestion measure is ignored then the results are counterintuitive to our beliefs that congestion is a bad. Accounting for spatial autocorrelation is also important particularly for this study area because in the last decade open space has been developed into small

clusters of neighborhoods and subdivisions. The characteristics of these subdivisions that are shared by property owners but not measured by the data are important.

Generalized measures of congestion seem likely to reflect an overall pattern of trips. While accessibility may not be completely defined by the level of congestion it is a very important component of it. This research suggests that by simply looking at the role congestion plays in the household's commute may underestimate congestion's true influence. Instead, suggesting that congestion affects a household's expected mix of trips, including the commute, better captures congestion's total disamenity effect. Past work has largely ignored this additional role for congestion. These results indicate it is important.

Chapter Four

4.1 Introduction

This research evaluates how household attributes affect the sensitivity of each adult member's travel choices to traffic congestion. Each household's time constraints are in many respects unique because they depend on the household's composition (e.g. presence of children and their age distribution, whether the household is dual or single earner, and its work and non-work responsibilities). This paper evaluates whether observable household attributes are sufficiently important to affect how individuals from different types of households respond to congestion in the choices they make for non-work trips.

The analysis is undertaken using a random utility model that is estimated based on individual trip choices within a two day period. This framework allows choice alternatives to be based on both the objective of a trip and its timing. It also allows consideration of both the attributes of these choices and those of the individual and household that might be important to these decisions. For example, households with children are expected to behave differently than households without children. The results of the analysis for households in Raleigh, NC in 1994 indicate that individuals with a high opportunity cost of time are twice as likely to have their trip taking decisions impacted by congestion as those with low opportunity costs of time. Congestion decreases the probability of taking a trip by 2.58 times more when children are not present than if there is at least one child in the household.

Models describing trips can translate reports of past trip into economic choices in a number of different ways. Not all trips are the same. The ability to determine how

individuals respond to congestion relies on understanding the assumptions models impose in structuring individual choices when a trip is translated into a choice alternative. This process implies restrictions on how the choice set is defined. By controlling the characterization of substitution among alternative types of trips through the assumptions used to define the choice alternatives and the relevant choice set, it is possible to investigate how the analyst's characterization of the choice process influences the results describing an individual's response to congestion.

The information for this analysis arises from responses to a two-day travel diary collected by a sample of households in the Research Triangle Park of North Carolina in 1994. These data offer information on individual and household characteristics that can be used to determine whether heterogeneity in individuals' attributes affects their sensitivity to congestion measured through their non-work trips.

The literature on the determinants of trip taking behavior includes a number of analyses of household and individual travel behavior. The format of the data, typically a one day diary, requires that the analyst select, as a maintained assumption, a definition for the choice alternative the individual is making. Often this is described based on one dimension of a trip. Trips are heterogeneous. As a result, the characterization of specific features of choice alternatives may well be important to the results from empirical models. That is, conclusions about what constitutes an adequate description of the determinants of individuals' choices will depend on how trips are translated into choice alternatives. A temporal and spatially delineated measure of congestion is also developed to evaluate the importance of congestion. Finally, the introduction of

individual and household characteristics allows consideration of factors hypothesized to be related to time constraints influences the effect of congestion on trip choices.

This paper begins with an outline of the conceptual model. Section 3 reviews the literature on trip decisions relating to purpose and timing for both work and non-work related trips. The random utility model is introduced in Section 4. The format of the data and summary statistics from the data are available in Section 5. The results, which indicate the importance of the definition of the trip and the degree of substitution across choice alternatives, are detailed in Section 6. A comparison of the effects of congestion on probabilities of taking specific types of trips and a measure of the incremental costs are described in Section 7. Finally, the summary of the finding and the implications of the research are described in Section 8.

4.2 Background for Modeling Short Term Trip Choices

In the long run, a household chooses a location to balance a number of aspects of the activities of daily living. For example, these can involve the work, leisure, and needs associated with the maintenance of the household. They are conditioned by housing and commuting costs, available public services, and supply of housing alternatives. This process implies that a long run equilibrium model, such as the hedonic property value framework, may provide a basis for describing how congestion influences these long run choices. In earlier research, I (2004) find support for this logic. That is, congestion does influence housing prices and that the overall impact of congestion is sensitive to the mix of trips a household completes.

These long run decisions are presumably based on an expected set of typical trips and anticipated time demands. In the short run, trips reflect the reality of immediate constraints which can be expected to be variable and perhaps less predictable. Housing choices are based on ex ante expectations for trip taking behavior. Individual reports on patterns of daily trips provide information, about actual trips. Thus the behavior describes ex post outcomes. In the process the analysis seeks to reconstruct the choice alternatives and important short term constraints to these decisions. It considers whether trip decisions provide sufficient information to distinguish individuals' responses to congestion conditional on the status of their household. Individuals are assumed to have prior knowledge about the level of congestion that they would face making short trips at different times of the day.

The data for this analysis are derived from trip diaries developed by the Triangle Transit Authority (TTA) in an effort to determine the feasibility of a light rail system in the Research Triangle Park. The TTA surveyed a sample of households about their trip making behavior over a two-day period. Individuals within a household recorded their own activity and trip taking behavior but the specific details of the trip decisions that might involve coordination or planning within the household were not provided. The survey assumes each individual makes trips independently of the rest of the members of the household. However, in practice this assumption is not likely to be true. Given the limitations of the data, this analysis can not develop an integrated model of household choice. Instead individuals are assumed to make trip decisions given their budget constraint and conditional on their household attributes. Thus, it is hypothesized that

individual and household characteristics will affect trip choices as well as the measured influence of congestion on these decisions.

When a model describes how an individual's time is allocated to completing activities, increases in congestion, are usually described as increases in the travel time. Time contributes to the implicit costs of each trip. Thus, congestion should increase trip costs. Individuals, if faced with no other constraints, should seek to avoid congestion. However, some activities can impose time specific constraints. For example, movies, banks, etc. are all regulated by schedules of some sort. Because individuals also have time specific constraints they are often forced to make trips during congested periods. These restrictions often arise due to other household members' needs or overall household needs. As a result interrelationships within a household can provide one potential explanation for the hypothesized link between household attributes and individual responses to congestion.

Ordinarily, it is assumed that individuals can trade off minutes saved in one set of activities for time that is used in other ways at different times of the day. In a static optimization model, it is assumed that an individual can respond to the increased costs of accomplishing activities by simply moving these tasks around within the time horizon that is implicitly underlying the model.

A significant limitation of the static optimization model is that it ignores schedules. There are scheduled times for certain activities. While there has been an increased flexibility in the work schedule, this has certainly not been uniform. It has lead to some spreading of the peak periods. The majority of employers only offer an earlier

arrival. These options imply a morning commute has a longer peak interval. Few employers allow their employees to telecommute or displace their work hours to the evening. Furthermore, this increased flexibility only pertains to the work schedule.

What appears to be in many instances an even greater restriction to individuals is the scheduling of non-work activities. Banks, dry cleaners, daycare, etc are only open at particular times of the day that typically coincide with the 9 – 5 workday. Discretionary activities like meal and shopping are more flexible with wider bands of time for accomplishing these objectives.

As a result it is reasonable to hypothesize that some households are more likely to experience schedule constraints because of their specific characteristics and will be less able to adapt to congestion. By contrast those less dominant schedule constraints should be able to re-allocate activities in response to time periods with congestion. Thus households' responses should be associated with flexibility and adaptability. Moreover, individuals may respond to congestion differently depending on the activity they are participating in.

Several individual and household factors are hypothesized to be influential in trip decisions. Work schedule flexibility is expected to play a large role in determining the timing of non-work activities. If an individual has a fixed work schedule then they can complete their other activities only during periods that don't conflict with the work schedule. Individuals with greater freedom in work times will not be faced with these limitations.

The age of the individuals may also be a factor. Both the young and the old are sometimes limited to the times that they can make trips. Teenagers have fixed school hours and curfews that they must adhere to and the elderly may be constrained by physical conditions that limit their ability to drive or participate in activities in the evening. Because these constraints are not reflected in the conventional model, both groups tend to engage in activities before the late evening.

Household circumstances also place constraints on the scheduling of some activities. Marital status, the number of children, and the number of available vehicles all can limit the number, purpose, and timing of trips. For example, children, less than driving age, are not treated as trip making individuals. Rather they can be considered as additional travelers that have activity needs. Their needs help to define household specific constraints, i.e. daycare, school, shopping, etc. In most instances, there is little schedule flexibility in the trips for children. This inflexibility arises from the interaction of a parent's work schedule together with the timing of a child's needs. The combination may imply certain trips must be completed during peak periods regardless of the expected congestion.

The objective of the analysis is to test the importance of individuals' and household constraints as they are proxied by household characteristics on the measured importance of congestion for the trip choices. It is hypothesized that as an individual's responsibility for other members of their household grows, congestion will be less influential in their trip choices.

An analyst's ability to detect the effects of congestion on individual choice at the level of a trip is determined partially by how the choice alternatives are specified. A trip can be decomposed into several components: purpose, timing, mode, and location. The choice set can be defined as a subset of those components or it could be all-inclusive. This definition depends on the character of the data and how the analyst controls for the substitution among alternative types of trips. Therefore the translation of trips into choice alternatives is a fundamental component of the description of behavior.

Given the available information, the choice set can be defined several ways. The choice could be among activities for a given time period or choices among time intervals for a given activity. Expanding the choice set to the simultaneous decision of activity purpose and timing is thought to most closely resemble actual individual behavior. Each step together with the modeling framework may imply attributes for the substitution possibilities among alternatives. That is, these modeling decisions will be especially important because they can influence the implied patterns of substitution across choice alternatives.

4.3 A Review of the Literature

Trips are heterogeneous. To appreciate the potential importance of this perspective this review considers the literature primarily from two perspectives, the definition of the choice set in relation to the trip and the characterization of congestion.

Table 4.1 highlights a few features of the literature that are developed in more detail below. These discussions focus on studies that used trip data from short term

diaries. Both work and non-work studies are included. The table highlights the type of trip, the choice set, the attribute that most closely measures congestion, and the socio-demographic variables included in the analysis.

Table 4.1 A Recap of departure time and activity studies⁸⁴

Authors	Work/ Non-work	Choice Set	Do nothing alternative?	Congestion Measure	Socio-demographic variables
Small (1982)	Work	Twelve, 5 minute periods, am peak	No	Schedule delay, travel time	Interaction of congestion measure with dummy for one person household, carpool, employment status, flex and inter
McCafferty and Hall (1982)	Work	Two time periods, pre and post pm peak, and pm peak	No	Travel time	Income, workplace flex, mode, # of kids, and # of work trips/week
Steed and Bhat (2000)	Non-work	Six time periods throughout entire day	No	Travel time, varied by peak and off peak only	Sex, Ethnicity, age, income, number of kids, employment status
Hamed and Mannering (1993)	Non-work	1) Stop on the way home or go straight home 2) Four activities: shopping, free time, private business or chain of trips	Yes No	N/A	Age, gender, car ownership, household size, children Departure time, income, mode, # children, employment
Lawson (1998)	Both	Activity choice: Must be able to be produced at home or away from the home.	Yes (stay at home)	N/A	AM peak, PM peak, male, age, household size, employed, household income

Small (1982) was the first to report an analysis of the departure times for trips to work.

The underlying focus of his study is to estimate the trade-off between congestion, and the associated longer travel times, versus changing the departure time. This tradeoff implies incurring “wasted” or excess time from arriving for work early or incurring a penalty by

⁸⁴ These studies were selected for the review because they all used trip survey data.

arriving for work late. He finds congestion affected the scheduling of trips. On average, urban commuters shift their departure times to work by 1 to 2 minutes earlier or by 1/3 to 1 minute later in order to save a minute of travel time. The penalty associated with late arrival is larger than arriving at work early. He also finds considerable variation depending on family status, occupation, mode, and the employer's flexibility. For example, arriving early appears to be less onerous for people from single households. Small's work prompted others to follow with additional departure time to work studies ((McCafferty and Hall (1982), Mannering (1989), Mannering and Hamed (1990)). In most instances, travel time is an important influence in the choice process.

The past twenty plus years have seen changes in the adherence to work schedules. Employers have started to adopt a staggered work week or flexible work schedule. In 1997, more than 25 million workers, or 27.6% of all full-time wage and salary workers varied their work hours to some degree (Beers, 2000). Nonetheless these options are largely based on informal arrangements. Only about 6% of employees have formal flexible work schedule arrangements. This is about twice as many as in 1985 (see Table 4.2). Small and the others' departure time studies were completed prior to this new trend in flexible work schedules, therefore it is not surprising that these studies found little temporal substitution in departure time choices.

Table 4.2 The percentage of population who have access to a flexible work schedule, either informal arrangements or formal

	1985	1991	1997
Total, > 16 years old	12.4 %	15.1%	27.6%
Men	13.1%	15.5%	28.7%
Women	11.3%	14.5%	26.2%

The departure time to work studies face another limitation. In most instances, the authors create choice occasions that were only five (Abkowitz, 1981) or ten minute intervals (Hendrickson and Plank, 1984) before work began and at the end of the work day. Reporting errors may compound the reliability of the perceived choices from these responses, especially with smaller time intervals. While individuals are asked to record their exact departure time, they tend to either round up or round down when recording these times. The results in these studies, relying on these data, may not be behavioral responses to congestion but simply a by product of rounding errors. More recently, there has been more emphasis to avoid the errors introduced with rounding and the ad hoc creation of time periods by estimating departure choice as continuous-time model (Bhat and Steed, 2002).

Recently researchers have investigated the factors that influence the choice of departure time for non-work studies. Kumar and Levinson (1996) in a purely descriptive study use responses from the National Personal Transportation Survey (NPTS) that collected detailed information on trip making behavior for a sample of households in the United States. This survey is administered every five years. The authors are interested in the factors that influenced departure time for both work and non-work trips. They hypothesize that trip making behavior on Saturdays is different from that on Sundays as well as weekday trip behavior. However, weekdays are expected to be similar. They also expect that workers will tend to perform shopping and other activities on the way home from work, while non-workers will tend to shop outside of the peak commuting hours.

Their findings are consistent with these hypotheses. Non-work trips for workers are at their highest levels during the peak evening commute as well as lunch time. Non-work trips for non-workers are made primarily between 10am and 4pm. Trips made on Saturday peak at noon until 6pm and then slowly declined. While this study is only a descriptive analysis of trip behavior and does not include any household level characteristics with the exception of employment status, it does provide some evidence that there are dissimilarities in departure times between the weekday and weekends and between workers and non-workers.

Steed and Bhat (2000) model departure time choice for home-based non-work trips using responses from a one day trip diary collected from a sample of households in the Dallas/Ft. Worth area in 1996.⁸⁵ They test the effect of travel time and various socio-demographic variables on departure time choice with four separate models. Each model is distinguished based on the purpose of the trip that was made: social/recreational, shopping, personal business and community activities. Time is broken into six periods: 12am – 6:30am, 6:30am – 9:00am, 9:00am – noon, noon – 4pm, 4:00pm- 6:30pm, and 6:30pm – midnight. They explore two different model structures, the multinomial logit model and the ordered generalized extreme value (OGEV) structure.⁸⁶ They find that based on the model's fit to the data the multinomial logit was adequate in representing the choice of departure time.⁸⁷

⁸⁵ No information was provided on the days the surveys were administered, including if the survey was extended to weekend trips.

⁸⁶ OGEV allows for an increased degree of sensitivity between temporally adjacent departure time periods.

⁸⁷ The dissimilarity parameter estimated from the OGEV was greater than one for three of the four activities which is inconsistent with utility theory.

Their results are not consistent with their proposed hypothesis that an increase in travel time during a specified time period would result in a decreased probability of taking a trip during that period. Only in the case when the trip was taken for recreational purposes was travel time a negative and statistically significant influence on trip choices. They find that gender did not have an important role in departure choice. Employment status is influential in the choice process; employed individuals and students were more likely to participate in non-work activities during the latter part of the day. Whereas self-employed individuals tend to sandwich recreational and shopping between the a.m. peak period and the p.m. peak period.

The construction of the travel time variable in this study may have introduced some errors in the variable. Travel times are assigned by calculating the time required to get from the origin to the destination Traffic Analysis Process (TAP) zones during only peak and off peak periods. The actual travel time for completing a trip during all six of the periods was not available, but instead an algorithm was used to calculate the expected time given normal conditions on the road during the two periods of the day. This time measure does not vary over all six periods, only over specified peak and off peak periods. The information used in the current analysis for Wake County suggests this assumption may be inadequate. Traffic volumes do indeed vary over all periods implying that individuals are faced with varying conditions throughout the entire day.

Wachs (1987) finds that women make shorter work trips, use transit more and make more trips for the purposes of providing travel services for others and drive fewer miles than men. He finds that employed women made more trips than non-employed

women. Bhat (1997) finds that older individuals are more likely to participate in at-home activities than out of home. And they are less likely to participate in recreational behavior than social or shopping activities.

Gronau (1977) finds that when income increases, households are likely to get assistance in the production of household services, i.e., eating out, dry cleaning, car maintenance. Golob (1997) finds that accessibility is an important determinant in activity choice. He considers the total retail employment locations within one mile of the residential location and found this to be a factor in activity participation.

Hamed and Mannering (1993) investigates the post-work activities of individuals in several steps. They first consider the choice to participate in an activity; there were two alternatives, go straight home or do something else. After selecting all of those individuals who did engage in an activity the authors attempt to describe the choice of which activity to engage in: shopping, free time, personal business, or a chain of trips.⁸⁸

They find that older people tend to complete activities shortly after work and then remain at home for the rest of the evening. Males are more likely to go directly home. As might be expected, the ownership of a car allows additional flexibility and increases the likelihood of going home after work. The size of the household and the number of children has little effect on trip chaining.

The results from the second choice process found that younger people have a higher propensity to shop than older individuals. Departure time from work was an

⁸⁸ They estimated the travel time to these activities and then used a duration framework to model the travelers' home-stay duration. Of relevance to this paper are the first two steps: the household and individual factors that influence activity choices.

independent variable and was found to be significant. The estimates for this variable varied over the activity alternatives. However, they did not find significant effects from income, mode, the number of children, or the number of employed individuals in the household.

Lawson (1998) tests the influence of socio-demographic influences on activity choice. The choice alternatives consisted of only those activities that could be produced either at home or out of the home. The author decomposes the choice set into the following alternatives: work, maintenance (meals, household business, household maintenance, and household obligations), and discretionary activities (exercise, rest and relaxation, and amusement). The results suggest that men are more likely to complete activities out of the home. Furthermore, full-time working status and higher incomes also results in an individual completing activities out of the home. The timing of the activities also matters. Departure time is again an independent variable. Morning peak has a positive influence on selecting out-of-home substitutes while the evening peak has a negative influence.

The literature review suggests that the factors that influence departure time choice for trips to work have been subjected to considerable research. However, there has only been one comparable study that describes the factors involved in departure time choice for non-work activities. Furthermore, the results aren't consistent with the proposed hypotheses. Thus, it is not possible to develop expectations for the measured effect of travel time, congestion, and household factors on departure time choice.

The inconsistency in the results describing the effects of travel time as well as some household attributes on trip choices, across most of the studies discussed, could arise from several factors. To test the hypothesis that congestion affects trip choice the variables used to measure congestion directly or its proxy measures needs to be clearly defined. Ideally the congestion measure would vary temporally over all choice alternatives and represent as nearly as possible the actual conditions an individual faces while making trips.

The activity choice studies recognize that the timing of an activity may be important; several included departure time as an independent variable, which arguably may be endogenous to the specification. For the most part, studies restricted the choice occasions to completing activities at limited times of the day (i.e., am peak, pm peak, after work). Either the authors omitted a time distinction or defined time composites arbitrarily. That is, the framework attempts to evaluate the domain of time intervals for trips. When a set of intervals is defined in too restrictive terms it implies that individuals are not able to consider the option of completing an activity at other times throughout the day. There is no a priori basis for evaluating whether this limitation is in fact present. Thus it may well incorrectly restrict the substitution patterns for the choice alternatives. Finally, with the exception of Small's work, the literature generally does not consider the full implications of the estimates. A measure of the marginal cost of congestion or the added time associated due to congestion would provide a basis to compare findings across studies.

4.4 Conceptual model

This analysis hypothesizes that time-varying congestion will influence the impact of various individual and household characteristics on an individual's choice of a trip. The definition of choice alternatives will examine features of trips in effort to describe how people consider the object of choice intended in advance of when a reported trip was undertaken.

Transition from Trips to Choice Alternatives

A key element in this research is the transition from a trip to a choice alternative. The analyst is reconstructing a choice process with ex post outcomes. There is a need to consider how the individual who reported making the trips actually structured the alternatives involved in the decision process that led to the observed choices. Ideally, the transition from a trip to the definition of a choice set captures all of the alternative options the individual considers when deciding to take a trip.

Presumably a trip is motivated by a desire to accomplish something. The components of the trip may involve some consideration for the purpose of the trip, the timing of the trip, or an activity/timing composite.⁸⁹ By translating a reported trip to a choice we can evaluate what can be learned from the RUM model. For example, by limiting the choice to only the activity purpose, household constraints that would highlight the time pressures of the household would probably not be influential in the

⁸⁹ Other components of a trip choice are important, for example, the trip destination and mode choice. However, there were no available data on the actual locations individuals visited. In addition, because of the limited public transportation alternatives in the study area, mode choice was not an interesting choice. Most of the individuals in the sample completed activities in their cars.

choice process but likely would be important in the timing of the activity or the composite choice of both timing and activity purpose.

The definition of the choice set is also important. This process entails defining time periods and activities or composites of the two. Several considerations arise when deciding how to define the choice set when individuals are choosing an activity purpose and/or timing of the activity. A primary goal of this research is to assess the role of household circumstances in trip decisions. As a result, it seems likely that these features will have the greatest influence (at the trip choice level of analysis) for trips that involve non-work activities.

The timing of a trip requires further clarification. What do individuals consider as the timing of the trip? It could potentially be the time they depart for the activity, or the day of the week, or some composite of both. It is assumed that the effect of household constraints on an individual's trip taking behavior generally will be the same for weekdays. Most of the individuals in this study did not work weekends. In addition, children are not in school. Thus, household constraints are not expected to have the same influence on weekend travel behavior. By separating the sample into weekday and weekend trips, we can better determine an individual's sensitivity to congestion.

The choice set defines the full range of choice alternatives. The choice alternatives are first defined separately based on two criteria: the purpose of the trip and the timing of the trip. Then composites of the two choices are defined as choice alternatives. The survey responses were organized into a total of fourteen activities but several of the activities had very few participants. For the purposes of this study, the

fourteen activities were aggregated into four activities. Individuals are assumed to participate in one of four activities outside of the home: personal business, amusement, shopping, or meals. A description of the activities selected from the survey is shown in Figure 4.1.

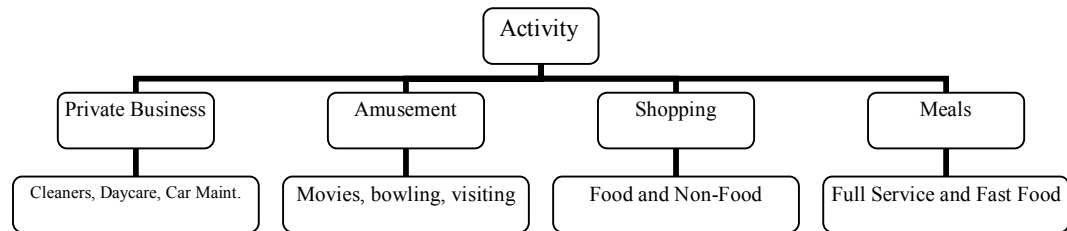


Figure 4.1 A description of the aggregation of activities

The survey collects the exact departure time for each activity.⁹⁰ Generally, the literature has limited the departure time choice alternatives by aggregating the choice of departure time to only peak periods and off-peak periods. However, it is expected that individual choices are based on more detailed time periods of the day and that household circumstances will influence this more specific range of departure times. For example, it is likely that household circumstances do not play as large of a role in lunch time trips than those trips made during the p.m. peak period. In this study, individuals can depart for an activity during one of five periods: a.m. peak, daytime off peak, lunch, p.m. peak, and evening, within a given day.

⁹⁰ Because the exact departure times were elicited in the survey there is a risk of rounding or other reporting errors. For example, of the 2,811 weekday trips recorded, 1,784 began exactly on the start of the hour, fifteen minutes past the hour, thirty minutes past the hour or forty-five minutes past the hour.

The decisions of the choice set and the full range of choice alternatives determines the substitution possibilities implicit in the model. Thus these decisions affect how congestion can be measured and how it varies. The best measure of congestion would include the travel time required to get to all activities at all times of the day. This travel time would be an outcome of the distance required to get to each of the locations of the four activities as well as the localized congestion at the time of departure. However, travel time is only available for the actual choice and not for any of the other alternatives. As a result, two measures are used to proxy for this unobserved measure of congestion. The proxy measure depends on the definition of the choice alternative. If the choice is specified to be one of the four activities, then the distance from the residential location to the activity is included as a proxy for the activity varying travel time. If the choice is specified as only the timing of the trip, then the number of cars on the road at that specific time of the day proxies for the time varying measure of travel time. If the choice is specified as the composite of activity and departure time, then both the distance to the activity as well as the number of cars on the road at the specified time of day are included.

RUM Model

These different characterizations of the choice process are modeled within a random utility framework. The indirect utility function in equation (4.1)

$$(4.1) \quad U_{m,n,i} = V_{m,n,i} + \varepsilon_{m,n,i}$$

is an additive function consisting of a deterministic part, $V_{m,n,i}$ and a random component, $\varepsilon_{m,n,i}$, which captures the heterogeneity hypothesized to be associated with individual characteristics or constraints. The random component is known from the individual perspective but not from the perspective of the analyst. The subscript m denotes the individual in household n making trip choice i for $i \in J$. The set of alternatives, J , depends on the features describing the attributes of a trip. An individual, m , in household, n , will choose choice i over an alternative j if:

$$(4.2) \quad V_{m,n,i} + \varepsilon_{m,n,i} > V_{m,n,j} + \varepsilon_{m,n,j} \text{ for } i \neq j$$

The probability an individual chooses i over j is:

$$(4.3) \quad \begin{aligned} P_{m,n,i} &= \Pr(V_{m,n,i} + \varepsilon_{m,n,i} > V_{m,n,j} + \varepsilon_{m,n,j}) \text{ for } i \neq j \in J \\ &= \Pr(\varepsilon_{m,n,j} - \varepsilon_{m,n,i} < V_{m,n,i} - V_{m,n,j}) \text{ for } i \neq j \in J \end{aligned}$$

If we assume that the ε 's are i.i.d, extreme value, then this is a closed form expression for the probability of each choice alternative being selected as in equation (4.4).

$$(4.4) \quad P_{m,n,i} = \frac{\exp(V_{m,n,i})}{\sum_j \exp(V_{m,n,j})}.$$

Model Specification

The logit's conditional indirect utility function reflects an individual's time and income constraints. An individual spends his or her day working, participating in non-work activities that involve travel, and enjoying leisure. The amount of time spent traveling depends on the distances to the activities selected and the congestion experienced when the trips are undertaken.

Each individual's time/budget constraint is unique due to the individual and household factors that structure the types of activities that they engage in. For individuals that are constrained by household circumstances, time can not be freely traded with the wage because of scheduling rigidities that they face from the needs of other members of their household. Furthermore, because the analysis is limited to non-work trips, the wage can not be defined as the opportunity cost of time the individuals in this study.

The primary hypothesis to be tested in this analysis maintains that there is an interaction between congestion and individual and household attributes that determine the impact of congestion on trip making. This is introduced in the model by creating interaction terms between congestion and each of the observable household and individual features.

If we assume that utility is linear in parameters then:

$$(4.5) \quad P_{m,n,i} = \frac{\exp(\phi_i(c_i, d_i) + \theta\alpha_m c_i + \eta\lambda_n c_i)}{\sum_j \exp(\phi_j(c_j, d_j) + \theta\alpha_m c_j + \eta\lambda_n c_j)}$$

where t_i is the time spent traveling for trip i . The time spent traveling is a function of congestion, c_i , and distance, d_i , such that $\frac{\partial t_i}{\partial c_i} > 0$ and $\frac{\partial t_i}{\partial d_i} > 0$. α_m and λ_n are vectors of individual and household characteristics respectively. It is hypothesized that the elements of θ and η , associated with household and individual characteristics that constrain individual choices from equation (4.5), will be positive. This suggests that

individuals will be less responsive to congestion. The elements, θ and η , related to attributes that increase a household's flexibility should be negative.

While the logit model is attractive for several reasons one assumption is quite restrictive. The logit model implies that unobserved factors are uncorrelated over alternatives (Independence of Irrelevant Alternatives (IIA)). Correlation among choice alternatives in extreme corner solution models can be interpreted as reflecting substitution. One of the most general approaches for allowing substitution is through the random parameters logit (RPL) framework.⁹¹ The RPL allows for the unobserved factors to follow any distribution. This model does not face the restrictive IIA assumption and also allows for heterogeneity in unobserved factors.

The characteristics of this study make it particularly suited to the RPL because there is a possibility of variation in three dimensions – the specification of the trip, the definition of the choice alternative, and its implication for individual choice. If, after controlling for the unobservable features of households and individuals that may be

⁹¹ The RPL is the integral of standard logit probabilities over a density of parameters. If we generalize the original equation (1) to:

$$U_{m,n,i} = \beta_m' x_{m,n,i} + \varepsilon_{m,n,i}$$

then the coefficients vary over decision makers in the population with density $f(\beta)$, this density is a function of parameters that represent the mean and standard deviation, b, s respectively of β . The decision maker knows her value of β_m and $\varepsilon_{m,n,i}$ for all i and chooses alternative i if and only if $U_{m,n,i} > U_{m,n,j} \quad \forall i \neq j$. The researcher knows the $x_{m,n,i}$'s only, therefore the probability that individual m in household n picks choice i is

$$P_{m,n,i} = \int \left(\frac{\exp(\beta' x_{m,n,i})}{\sum_j \exp(\beta' x_{m,n,j})} \right) f(\beta) d\beta$$

By specifying a distribution for the coefficients it is possible to estimate the parameters of the distribution, (b, w) .

influential in trip choices, there is still an effect of observable features of households, then these results help to convey congestion may be important. The RPL will be used to estimate influences of individual and household attributes on the impact of congestion on the choice of a trip.

Hypotheses

The analysis considers several hypotheses. Three models provide alternative characterizations of individual choice: activity, timing, and the composite of both. Furthermore, two additional controls are introduced for the choice alternatives and choice sets. The analysis investigates the influence of the same household and individual characteristics on a sub-sample of trips that are distinguished by trips made on a weekday versus those made on the weekend. In a separate model, the analysis then controls for residential location by creating a sub-sample that separates households that live inside the central city from those households that live outside the city. It is hypothesized that the trip making behavior for these two sub-samples will be different. Finally, the analysis argues that the individual and household influences on choices are not simply a reflection of unobserved heterogeneity. After controlling for the unobservable features through RPL these observable features are hypothesized to be important in the choice process.

4.5 Data

Five data sets are used in the estimation of the conditional logit and the random parameters logit models. In 1994, the Triangle Transit Authority in Research Triangle Park asked a sample of residents to record their activity and trip taking behavior over a

two day period. This period varied over the course of a year. Respondents first participated in a phone interview and then were mailed a travel diary that requested records of their behavior for a specified two day period. In addition, the survey also elicited details regarding a range of household, personal, and vehicle information. The basic observational unit is a trip or activity. The participants' residences are geo-coded. Because only the residential locations are geo-coded, only non-work trip trips that originated from the home are used in this research. In addition, only trips that were made with a vehicle are included. Table 4.3 describes the composition of trips by the trip's origin. Summary statistics for the survey and a selection of the variables are detailed in Table 4.4. Table 4.5 provides a description of the demographics.

Table 4.3 The number of trips taken by trip origin

Type of trip	Number of trips
Home-based work	1,556 trips
Home-based other	3,676 trips
Non-home based	8,871 trips

Table 4.4 Descriptive statistics from TTA data⁹²

Variable	Average	Std Deviation
Number of children	1.06	1.13
Number of cars/driver	1.21	0.52
Age of respondent (years old)	40.32	13.48
Hourly wage (\$)	11.56	7.17
Activities per day	15.03	8.92
Licensed Drivers	2.01	0.79

⁹² Yearly income was reported. Hourly wage was calculated as yearly income divided by 2000 hours.

The second and third sets of data are collected separately by the North Carolina Department of Transportation (NCDOT). The first reports average annualized daily traffic (AADT) counts recorded at 5,400 traffic count stations in Wake County. A vehicle counter is placed by a segment of roadway for approximately two or three days several times a year. The number of vehicles that pass by that station per day are recorded and then averaged over the measured days for the final AADT count. The counts are adjusted seasonally if appropriate. In addition, these traffic count stations are geo-coded. While the data are collected approximately every two years this analysis considers the information exclusively from 1994.

Table 4.5 The composition of respondents participating in the TTA travel survey

Demographic Group	Percentage of Total Respondents (3,676 observations)
No Children	42.79%
Single	18.82%
Married	23.97
One Child	15.32
Two Children	27.91
Three Children	10.15
Four + Children	3.83
Less than 35 years old	30.96%
Between 35 yrs old and 60	62.78
Older than 60 years old	6.37
Live within Raleigh Beltline	35.01%
Live outside Raleigh Beltline	64.99%
Male	44.12%
Female	55.88%

The second NCDOT data consist of traffic counts that are recorded every fifteen minutes, from 6:00 a.m. until 9:45 p.m., at nine different intersections in Wake County. Five departure time choices are considered in the analysis: the AM peak period, from

6:00am – 9:15am; the off-peak period, 9:15am – 11:30am and 1pm- 4pm; lunch, 11:30am – 1pm; PM peak; 4 – 6:30pm; and evening, 6:30pm – 9:45pm. As a result, these records were constructed in a conformable format. The counts are specified according to the type of turn a vehicle made through the intersection. The individual directions through the intersection are not assumed to be important as the number of cars that passed through. The data from eight of the nine intersections are reported as an average of two consecutive weekday vehicle counts. These were recorded at different periods from 1997 to 1998, the earliest years available. The vehicles at the ninth intersection are recorded on a Saturday, the only weekend observation recorded before 2001. Each of the nine intersections was geo-coded and matched to a traffic count station.

Rather than using actual vehicle counts recorded from the intersections, the percentage of cars that drove through the intersection during specified periods of the day was used as a summary of activity. Because data were only collected at nine intersections, in many instances the closest intersection from a home can be quite distant. Therefore, the measure of vehicles may not represent the number of cars on the road near the home. However, the variation in the percentage of cars across time periods is relatively constant across intersections. Attaching the percentage of cars that pass by the nearest intersection seems more appropriate than the actual vehicle counts. A description of the distribution of cars per hour through the nine specified intersections can be found in Table 4.6. Table 4.6 suggests that peaks in traffic occur at 6:00 – 9:15 am and 4:00 – 6:30 pm and lunch time. These peaks in traffic do not exist on Capital

Boulevard, the weekend observation. Figure 4.2 illustrates the disaggregated flow of cars through each of the nine intersections.

The final time varying measure of congestion is equal to the AADT traffic count weighted by the percentage of vehicles that went through the nearest intersection.

Records for each of the time distributions of traffic at the closest intersection were assigned to the closest traffic count station. Using the shortest distance based on the actual road network between a residential location and a traffic count station, it allows an estimate for a time varying index of congestion to be developed.

Table 4.6 Proportion of vehicles driving through an intersection per hour over five time periods⁹³

Time\Intersection	Gorman Rd	Tryon Rd	US 401	Perry Rd	Milbrook Rd	Calvary Dr.	US 64	Glenwood Ave	Capital Blvd
6:00am - 9:15am	0.080	0.085	0.086	0.074	0.071	0.081	0.070	0.087	N/A
9:15 - 11:30am and 1 – 4pm	0.061	0.068	0.070	0.068	0.073	0.060	0.067	0.064	0.111
11:30am to 1:00pm	0.064	0.079	0.081	0.072	0.087	0.060	0.074	0.080	0.112
4:00 pm to 6:30pm	0.109	0.097	0.092	0.105	0.096	0.103	0.100	0.096	0.099
6:30 pm to 9:45pm	0.051	0.041	0.039	0.042	0.041	0.053	0.053	0.042	0.043

The fourth data set comprises all stores and services in Wake County. The stores that fall under the purpose of the four specified activities in this study: personal business, amusements, shopping, and meals were geo-coded in relation to the residential properties from the survey. Using Arcview Network Analyst, the distance from the residential property to the five closest stores and services within each grouping of activity was calculated. The average distance across the five closest stores and services was used as a

⁹³ The last column in the table, Capital Blvd, was recorded on a Saturday, from 9:00am until 9:45pm.

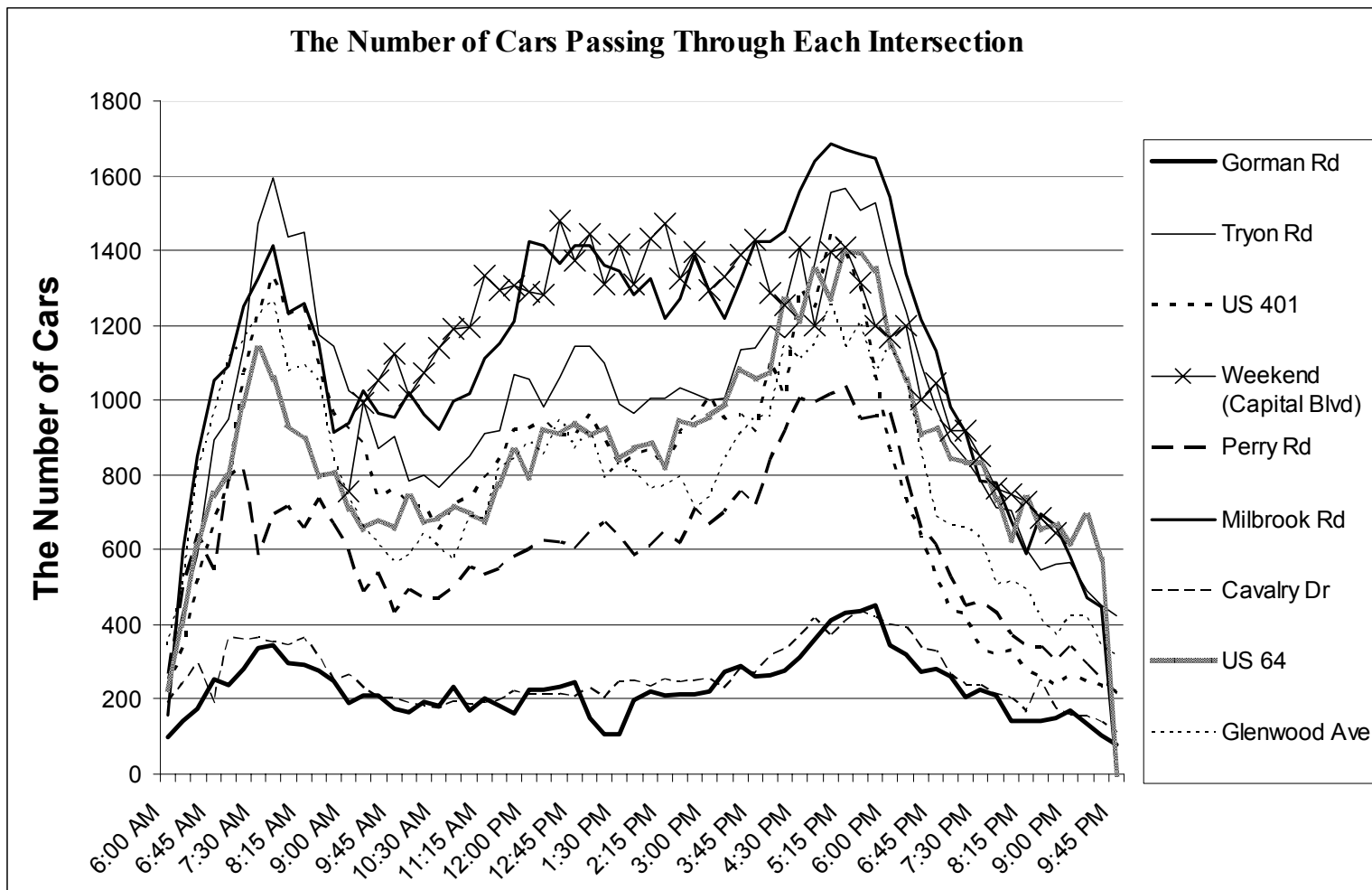


Figure 4.2 The flow of cars over each intersection by time of day

proxy for accessibility. The last data set consists of all geo-coded primary and secondary road networks in Wake County.

There are a total of 5227 observations. Of those 5227 observations, 3671 trips were made for non-work purposes. The trip taking behavior of individuals in this study over the course of a weekday are shown in Figure 4.3.

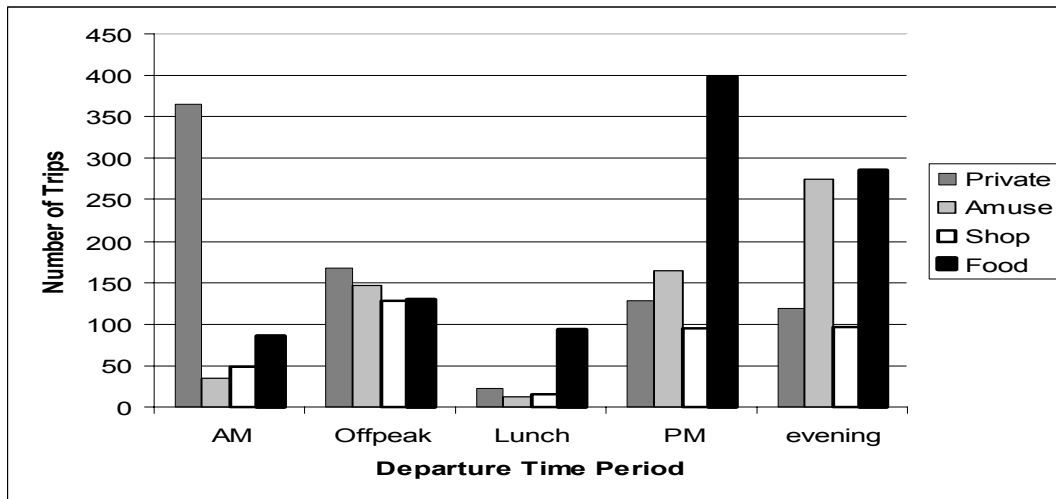


Figure 4.3 The number of trips taken by departure time and activity purpose, weekdays

4.6 Estimation and Results

Overview of Results

Three models provide alternative characterizations of individual choice. In the first, the alternative motivating a trip focuses on an activity. The second model considers the time period as the choice alternative that motivates a trip and then in the last it is a composite of time and activity. It is expected that household characteristics will influence the individual's sensitivity to congestion conditional on the specification of the choice.

When the choice is a composite of both activity and trip time, the choice set is further characterized by separating the sample into trips that are made during the week from the weekend. The estimates for these three models are developed with the simple conditional logit model.

Two different methods are employed to account for individual heterogeneity. Within the conditional logit framework, samples are separated by those households living within the city of Raleigh and those living outside Raleigh. This accounts for heterogeneity in trip taking behavior that is not captured with the observable features from the data. The purpose of this model is to investigate if household features alter individuals' responses to congestion differently for individuals living within the city limits than those living in the suburbs. The RPL is implemented as the final step in the estimation process. It is well suited for this research for two purposes. It is not constrained to assume IIA. Furthermore, it takes into consideration that individuals are heterogeneous. It is expected that after taking into account the unobserved heterogeneity of individuals, the observable features measured in the data from the survey will still be influential in the choice process. A summary of the five models tested is presented in Table 4.7. Detailed in the table is a definition of the choice alternatives, the elements in the model, the tests of hypotheses, and qualifying comments for each model.

Choices based on activity

The first model examines the influence of distance, congestion, and various household characteristics on activity choice. Each of the five departure time periods is treated as a

separate model. The full set of results is located in Table E1 in Appendix E. Distance is the only variable that varies over the choice alternatives. The time period specific congestion variable is considered as an alternative specific constant as well as the pure fixed effects, the number of cars per licensed drivers, the number of children, the age, gender and the hourly wage of the individual.

This formulation for modeling choice alternatives is not very informative. Distance is not an important influence in activity decision. It was expected that the probability of taking a trip would decrease as estimated distance increased. Congestion also does not seem to be influential in activity choice. The number of children does seem to have a small role in activity choice as hypothesized. It has a positive influence on taking private trips during the AM peak, off peak, and evening compared to trips made for meals, the normalizing choice. The fixed effects are highly significant suggesting that activity choice is explained by other factors specific to each activity but not readily measured with the information available in the survey.

Choices based on time

When the choice alternative is defined to include all five departure time periods, each activity was treated as a separate model and the full results are described in Table E2 in Appendix E. In this case, congestion can vary over the alternatives. Interaction variables between the household and individual characteristics and congestion are introduced to test how household constraints influence an individual's sensitivity to congestion. By construction, they also vary over the alternatives. Finally, fixed effects are included for

Table 4.7 A summary of conditional logit results when a trip is translated into an activity, time and a composite of both

Choice	Congestion Variable	Elements in Model	Results	Tests of Hypothesis	Qualifications
1) Activity (For a given time period, 5 total models)	Congestion does not vary over choice alternatives	Alternative varying distance; number of children; #cars; #kids; age; gender; opportunity cost of time; Alternative Specific Constant (ASC) for each activity (4)	No distance effect; ASC significant for most alternatives;	Congestion only significant for shopping (evening only); # kids only significant for off private activity (off peak, evening) and amusements (off peak);	Largely uninformative ASCs may be capturing the congestion effects
2) Departure Time (For a given activity, 4 total models)	Congestion varies over choice alternatives	Interaction variables: Congest*wage; Congest*#kids; Congest*#cars; Congest*age Congest*gender; ASC for each time period (5)	Congestion significantly negative (amusement and shopping models)	Congest*age negative significant (shopping), positive (meals); Congest*kids positive significant (shopping and meals) Congest*wage and congest*cars no effect	Congestion is influential for models describing discretionary activities (amusement and shopping) ASC's suggest that amusement trips favor the evening and meals are primarily evening activities
3) Composite of Activity and Departure Time	Congestion varies over departure time alternatives	Interaction variables: Congest*wage; Congest*#kids; Congest*#cars; Congest*age Congest*gender; ASC for each time period and activity (20)	Congestion (varying over time periods) and Distance (varying over activities) are negatively significant	Congest* kids and congest*age both positively significant Congest*wage significantly negative	Congestion and interaction effects are still significant even after including ASC's for each alternative. Congestion has negative effect muted by children and age for any activity/time combination

Table 4.7 Cont'd

4) Residential Location Sub Sample	Congestion varies over departure time alternatives	Alternative varying distance; Interaction variables: Congest*wage; Congest*#kids; Congest*#cars; Congest*age Congest*gender; ASC for each time period and activity (20)	Both congestion and distance have significant negative effects for city residents Only congestion is significantly negative for suburban residents	Congest*#kids only significant interaction variable for city residents Congest*#kids, congest*age, congest*wage, and congest*#cars are significant for suburban residents	Distance to activities is not an important influence for suburban residents perhaps because it was a major factor in residential location decisions. Household circumstances influence the role of congestion for suburban residents more than city residents
5) Random Parameters Logit	Congestion varies over departure time alternatives	Alternative varying distance; Interaction variables: Congest*wage; Congest*#kids; Congest*#cars; Congest*age Congest*gender; ASC for each time period and activity (20)	Congestion is significantly negative The standard deviation of congestion is significantly positive	Congest*#kids and congest*age both significantly positive	After controlling for unobserved heterogeneity, household circumstances still influence an individual's response to congestion

each of the alternatives. The evening departure time is the normalizing choice alternative.

The results indicate that congestion deters taking trips for amusement and shopping purposes and is a marginal deterrent for taking meal trips. However, it does not influence the decision to take a trip for the purpose of personal business. It may be reasonable to assume that personal business trips are made by prior appointment out of necessity and an individual has very little flexibility in completing these trips. Because a good portion of the personal business trips were for the purpose of dropping or picking up children, this generally can not be avoided and hence the individual is unable to respond to congestion.

Of the interaction variables, the number of children and age interacted with congestion are significant for only shopping and meal trips. As the number of children increases, the level of household responsibility also increases, creating further constraints on the licensed drivers in the household. Therefore, there is a limitation to how much the individual can respond to congestion. Because the coefficient is positive, this indicates that individuals are less responsive to congestion than they would be if they had no children.

The interaction between age and congestion is not as clear. The coefficient is negative for shopping trips and positive for meals. Age may not necessarily be the factor in departure time choice. Age may be a proxy for other household and individual factors such as employment status and perhaps the level of household responsibility. Therefore, there are potential effects in both directions. Regardless, the effects of congestion are

different based on age. Gender, sex, and availability of car use are all insignificant factors in the choice process. Finally, fixed effects are significant for all alternatives except for shopping in the AM peak period and personal business in the PM peak period.

Choices based on composites of time and activity

Table 4.8 describes the results from estimating the composite choice of activity and departure time. This definition for choice alternatives implied a total of twenty alternatives. The first column of Table 4.8 highlights the results of the conditional logit when congestion and household interaction effects are included, as well as fixed effects. Congestion does not appear to be influential in the choice process.

By disaggregating the data based on one set of conditioning choices, the day of the trip (weekday vs. weekend), congestion now appears to be influential. Furthermore, as hypothesized, several household attributes affect the role of congestion. Congestion is not a significant influence in weekend trips. However, distance appears to be an important factor in weekend trip making. The probability of a trip decreases as the distance to its location increases. Of the household attributes, only the interaction between congestion and gender is significant.⁹⁴ Because many people do not work on the weekend their schedules are generally more flexible enabling them to participate in activities throughout the entire day and also rescheduling activities if congestion is anticipated. The influences that affect trips made on the weekend appear to be different than trips made during the week.

⁹⁴ Gender is a dummy variable, female = 1, male = 0.

For weekday trips, congestion is a significantly negative influence but distance is no longer a factor. Both the interaction of congestion with the number of children in the household and age are highly significant. The coefficient on the number of children is positive as expected. The effect of congestion is muted by the presence of children reflecting a household's schedule inflexibilities. The coefficient on age is also highly significant suggesting that perhaps age is proxying for additional household responsibility not captured in the data. The interaction between congestion and wage also appears to be marginally influential. The negative coefficient suggests that individuals with high wages will be more responsive to congestion. They will tend to make trips during non-congested periods to avoid losing their highly valued time.

Two of the interaction variables consistently are insignificant. While hypothesized that women would be less responsive to congestion because they are usually the major caretakers of the children, the results do not indicate this with any significance. The number of cars per driver is insignificant. This may seem surprising but there is little variation in the number of cars per driver: 68.69% of the sample has one car per licensed driver, 14.6% has less than one car per driver, and 15.52% has between one and two cars per licensed driver. Furthermore, all trips were made using a personal vehicle, therefore there had to be at least one vehicle available to make the trip. It seems reasonable to expect this variable would be of increased significance in more urban areas where mass transit, walking, and biking, etc, were more available modes of transportation.

Table 4.8 Conditional logit results, by day of week, normalizing choice = meals evening

	Conditional Logit (All trips)	Conditional Logit (weekday trips)	Conditional Logit (weekend trips)
Congestion	-0.00011 (-.702)	-.000647* (-2.89)	-0.000172 (-0.54)
Distance	-0.0000041 (-0.37)	.0000099 (0.78)	-0.000052* (-2.13)
Congest*#kids	.00007914* (2.45)	0.000135* (3.40)	-0.000052 (-0.81)
Congest*gender	.000152* (2.09)	0.000078 (0.84)	0.000302* (2.47)
Congest*age	.00000733* (2.53)	.00000874* (2.38)	0.00000783 (1.54)
Congest*wage	-0.0000073 (-1.16)	-0.000010 (-1.83)	-0.000012 (-1.22)
Congest*#cars	-0.0000634 (-0.82)	0.000116 (0.80)	-0.000156 (-0.68)
<i>Alternative Specific Constants</i>			
Private AM	0.077579 (1.047)	0.2992* (3.47)	-0.5629* (-2.97)
Private Offpeak	-0.36111* (-4.341)	-0.4965* (-4.962)	0.3249* (1.98)
Private Lunch	-2.382* (-13.63)	-2.5152* (-11.24)	-1.6185* (-5.51)
Private PM	-0.97074* (-9.38)	-0.6983* (-5.70)	-0.8635* (-3.92)
Private Evening	-0.954147* (-9.54)	-0.8848* (-8.02)	-1.2695* (-5.26)
Amuse AM	-1.9150* (-13.149)	-2.0547* (-11.20)	-1.3000* (-5.16)
Amuse Offpeak	-0.6348* (-6.931)	-0.6439* (-6.02)	-0.1740 (-0.92)
Amuse Lunch	-3.0994* (-12.72)	-3.1282* (-10.53)	-2.4909* (-5.75)
Amuse PM	-0.73451* (-7.45)	-0.4507* (-3.86)	-0.6742* (-3.14)
Amuse Evening	-0.03351 (-0.431)	-0.0554* (-0.63)	0.0421 (0.25)
Shop AM	-1.8756* (-12.87)	-1.7494* (-10.69)	-1.9998* (-5.82)
Shop Offpeak	-0.606741* (-6.43)	-0.7860* (-6.81)	0.1925 (1.05)
Shop Lunch	-2.3481* (-13.39)	-2.9157* (-10.83)	-1.1002* (-4.24)
Shop PM	-1.1559* (-10.16)	-1.0138* (-7.36)	-0.6276* (-2.85)
Shop Evening	-1.1593* (-10.32)	-1.1179* (-9.00)	-1.3803* (-5.14)
Meals AM	-1.30405* (-11.67)	-1.1363* (-8.97)	-1.5595* (-5.93)
Meals Offpeak	-0.79385* (-8.518)	-0.7405* (-6.85)	-0.5157* (-2.67)
Meals Lunch	-1.08527* (-10.5)	-1.0610* (-8.63)	-0.6231* (-3.04)
Meals PM	0.116635 (1.46)	-0.4516* (4.65)	-0.0304 (-0.18)

Separating the sample by residential location highlights the role of other conditioning choices and provides a different methodology for accounting for unobserved heterogeneity in households. The data are grouped into two sub-samples with individuals living within the city limits and those living outside the city limits of Raleigh. Typically individuals who live in urban areas expect to complete most of their trips in close proximity to their home. Raleigh is not as urbanized as major cities such as New York, Chicago, etc. For example, the city of Raleigh's population is about 2,409 people per square mile and there are 1,053 housing units per square mile where as New York City has 66,940 people per square mile and 34,756 housing units per square mile.⁹⁵ As a result it is still expected that both congestion and distance will be more important factors in trip making behavior for people who live in downtown Raleigh.

Individuals who live outside the city limits in suburban areas expect that the locations of the activities that they participate in will be further away. By purchasing a home in a suburban area you are inheriting a longer distance to activities. This may indicate that it does not play a very large role in the decision to make trips. The results, described in Table 4.9, highlight these exact issues. Distance is a negative influence for individuals in the city but of little importance to those individuals living in the suburbs. Congestion is an important factor in both areas. Interestingly, age and wage are not influential for those individuals living inside Raleigh.

⁹⁵ U.S. Census 2000

Table 4.9 Choice of both activity and departure time differentiated by residential location

	Inside Raleigh	Outside Raleigh
Congest	-0.000568* (-2.27)	-0.001548* (-3.50)
Distance	-0.0000446* (-2.40)	-.0000019 (-0.11)
Congest*#kids	0.000124* (2.71)	0.000185* (2.47)
Congest*gender	0.0000709 (0.66)	0.0000303 (0.19)
Congest*age	0.0000057 (1.31)	0.0000179* (2.67)
Congest*wage	0.0000016 (0.17)	-0.000019 (-1.65)
Congest*#cars	0.000193 (1.12)	0.000601* (2.38)
Alt Specific Constants		
Private AM	-0.1633 (-1.60)	0.6184* (4.38)
Private Offpeak	-0.7296* (-6.34)	-0.4136* (-2.40)
Private Lunch	-2.8953* (-10.44)	-2.2395* (-6.34)
Private PM	-1.1198* (-7.55)	-0.2717 (-1.43)
Private Evening	-0.9190* (-7.66)	-0.8241* (-4.46)
Amuse AM	-2.4834* (-10.88)	-1.6625* (-6.01)
Amuse offpeak	-1.1674* (-8.66)	-0.2247 (-1.36)
Amuse Lunch	-3.090* (-10.31)	-3.7420* (-5.22)
Amuse PM	-0.9443* (-6.57)	-0.1705 (-0.92)
Amuse Evening	-0.2864* (-2.80)	0.0435 (0.30)
Shop AM	-2.0279* (-10.70)	-1.8674* (-6.11)
Shop Offpeak	-1.1117* (-8.16)	-0.5192* (-2.80)
Shop Lunch	-3.1275* (-10.35)	-2.8229* (-6.07)
Shop PM	-1.5055* (-8.89)	-0.5887* (-2.76)
Shop Evening	-1.4686* (-9.73)	-0.8999* (-4.59)
Meals AM	-1.2406* (-8.85)	-1.0377* (-4.82)
Meals Offpeak	-0.9561* (-7.70)	-0.5452* (-3.08)
Meals Lunch	-1.1202* (-8.40)	-1.0717* (-4.92)
Meals PM	.01007 (0.87)	0.8144* (5.28)
Number of observations	1113	1698

Treatment of unobserved heterogeneity

The final model is estimated with the RPL. The RPL is considered the most flexible because it is more general than the logit model and is not constrained to satisfy IIA.

Congestion is the only variable allowed to have a random coefficient and it is assumed to have a normal distribution with mean and standard deviation that are estimated. More specifically, the specification implies that the sign and magnitude of the effects of congestion (excluding interaction terms) will vary over trip-taking individuals.

Furthermore, it is used in this instance to determine if the observable features measured in the data still influence an individual's sensitivity to congestion even after controlling for the unobserved features not measured. The results from the RPL are described in the second column of Table 4.10, next to the logit results for a comparative evaluation.

Simulation was performed using one thousand random draws for each individual. The results indicate that even after allowing for variance in the effects of congestion, observable household features do matter. The estimated mean is significantly negative and the standard deviation is significant indicating that the coefficient does indeed vary in the population. The estimated mean and standard deviation of the coefficient provide information on the share of the population that places a negative value on congestion. This suggests that congestion is a negative inducement for 89% of the individuals. All of the additional variables remain the same sign and significance as detailed in the first column of Table 4.10.

Table 4.10 Choice: activity & time, last column = RPL

	Conditional Logit	RPL
Congestion Mean	-.000647* (-2.89)	-0.000799* (-3.11)
Congestion Standard Deviation		0.000616* (2.68)
Distance	.0000099 (0.78)	.0000097 (0.71)
Congest*#kids	0.000135* (3.40)	0.000174* (3.62)
Congest*gender	0.000078 (0.84)	0.00007 (0.69)
Congest*age	.00000874* (2.38)	.00000936* (2.06)
Congest*wage	-0.000010 (-1.83)	-0.000082 (-1.53)
Congest*#cars	0.000116 (0.80)	0.000166 (1.00)
<i>Alternative Specific Constants</i>		
Private AM	0.2992* (3.47)	0.3487* (3.76)
Private Offpeak	-0.4965* (-4.962)	-0.4498* (-4.24)
Private Lunch	-2.5152* (-11.24)	-2.4273* (-10.71)
Private PM	-0.6983* (-5.70)	-0.6939* (-5.59)
Private Evening	-0.8848* (-8.02)	-0.8817* (-7.91)
Amuse AM	-2.0547* (-11.20)	-2.0139* (-10.78)
Amuse Offpeak	-0.6439* (-6.02)	-0.6019* (-5.37)
Amuse Lunch	-3.1282* (-10.53)	-3.1177* (-10.42)
Amuse PM	-0.4507* (-3.86)	-0.4389* (-3.63)
Amuse Evening	-0.0554* (-0.63)	-0.0523 (-0.59)
Shop AM	-1.7494* (-10.69)	-1.7086* (-10.14)
Shop Offpeak	-0.7860* (-6.81)	-0.7370* (-6.18)
Shop Lunch	-2.9157* (-10.83)	-2.8637* (-10.61)
Shop PM	-1.0138* (-7.36)	-1.0032* (-7.14)
Shop Evening	-1.1179* (-9.00)	-1.1098* (-9.00)
Meals AM	-1.1363* (-8.97)	-1.0947* (-8.34)
Meals Offpeak	-0.7405* (-6.85)	-0.6885* (-6.07)
Meals Lunch	-1.0610* (-8.63)	-1.0069* (-7.93)
Meals PM	-0.4516* (4.65)	0.4600* (4.61)

4.7 Comparative Evaluation of Findings

Marginal Effects for Congestion for Varying Household Attributes

The signs and the statistical significance of the estimated parameters in the logit model provide a description of how congestion will influence the probabilities of taking a trip.

To test the hypothesis that the effects of congestion vary over different types of household, marginal effects and their respective standard errors are calculated to determine the complete influence of congestion as implied by each model's specifications on the probabilities of a set of well-defined trips.

The marginal effect of congestion defined as the change in the probability that individual n chooses alternative i over j given a change in congestion, c_{ni} is:

$$(4.6) \quad \frac{\partial P_{ni}}{\partial c_{ni}} = \frac{\partial V_{ni}}{\partial c_{ni}} P_{ni} (1 - P_{ni})$$
$$= (\beta_c + \beta_{kid} kids + \beta_{age} age + \beta_{wage} wage + \beta_{sex} sex + \beta_{car} car) (P_{ni} (1 - P_{ni})).$$

It is through the $\frac{\partial V_{ni}}{\partial c_{ni}}$ term that the hypothesis is evaluated. The change in the probability that individual n chooses alternative i over j given a change in congestion, c_{nj} is:

$$(4.7) \quad \frac{\partial P_{ni}}{\partial c_{nj}} = - \frac{\partial V_{ni}}{\partial c_{nj}} P_{ni} P_{nj}.$$

Given the results from the previous section, wage (opportunity cost of time), children and age appear to be significant. Therefore, the data were broken up into several groups within these three sets of demographic attributes. To test if the influence of

congestion was different for individuals with different wages, the sample was divided into two groups, those with a wage greater than \$12/hour and those with a wage less than \$12/hour. Household structure was divided into two groups, those households with no children and households with at least one child. Finally, to test if the influence of congestion varied by age, three samples were created: young individuals (16-35 yrs old), midlife individuals (35- 60 yrs old), and older individuals (older than 60). As a result of the configuration of the groups, an individual will appear in exactly one group for each of the three tests.

Each sub-sample was bootstrapped 100 times resulting in 100 estimates of the parameters for each of the seven sub-samples.⁹⁶ The marginal effects were calculated 100 times for every individual and then averaged over individuals within the sub-sample. The reported marginal effects, found in Appendix E, are the average over the 100 bootstrap replications. Standard errors are calculated using the average marginal effects over the 100 bootstraps, therefore $N = 100$ for each designated group, regardless of the sample size. Standard errors are not reported, for purposes of conserving space, but are used to test if the marginal effects differed over what are expected to be diverse demographic groups of individuals.

The marginal effects for these seven groups are reported in tables E3 – E9 in Appendix E. With the exception of the groups of individuals with children and the older group, the marginal effects are of the expected sign (negative on the diagonal, and primarily positive on the off diagonal). These results suggest that older individuals and

⁹⁶ Bootstrapping was completed within the conditional logit framework.

households with children are not flexible. Their schedules and their household constraints do not allow them to respond to congestion. For all other groups, individuals do respond to congestion and congestion decreases the probability of taking a trip.

To test for differences across groups, a simple difference in means test is used:

$$z = \frac{\bar{x}_1 - \bar{x}_2}{\sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}}}, \text{ where the } \bar{x} \text{ 's and } s \text{ 's are the mean and standard deviation of the}$$

marginal effects, respectively, for each group, and $n_1 = n_2 = 100$, the number of bootstraps.

Given the large amount of choice occasions, all of the off-diagonal terms of the marginal effect matrix are very small. Therefore, it is expected that there will not be a statistical difference across groups for these effects. It is expected that the responses by individuals with high opportunity costs of time to congestion would be significantly greater than individuals with a lower opportunity cost of time. In addition, it was also hypothesized that individuals without children would be more able to respond to congestion than those with children. Therefore the difference in the incremental effect of congestion on the probability of trips for a household with no children and a household with at least one child, would also be significantly negative. Finally, it was expected that individuals who are in their midlife could respond more to congestion than younger or older individuals because they would have established a professional career that allowed them flexibility in their travel behavior. Table 4.11 reports a summary of the results testing the differences between the diagonal terms across demographic groups. The full set of results is found in Table E10 in Appendix E.

Table 4.11 A summary of the differences in the marginal effect of congestion across different demographic groups

	Difference in Means Test (Marginal Effects)				
	High Wages– Low Wages	No Children – At Least One Child	(Age) Midlife - Old	(Age) Midlife - Young	(Age) Young - Old
Hypothesized Effect	Negative	Negative	negative	Negative	Negative
Number of occurrences when there is a significant negative difference (20 choice alternatives)	6 out of 20	20 out of 20	20 out of 20	0 out of 20	20 out of 20
Qualifications	High wage individuals are more responsive to congestion only during peak periods	At all times and for all activities, individuals with children are less responsive to congestion	At all times and for all activities, older individuals are less responsive to congestion than midlife individuals	There is no significant difference in responses between young and midlife individuals	At all times and for all activities, older individuals are less responsive to congestion than young individuals

Most of the results are consistent with the hypotheses. In six instances, there is a statistical difference between the two income groups. For all trips made during the PM peak period, individuals with high wages respond to congestion more than individuals with low wages. There are also different responses in the AM peak period for amusement and shopping. However, for the rest of the choices, there is not a statistical difference between the two groups. In addition, as expected, households without children are able to respond to congestion more than households with children. In all instances there is a clear statistical difference. Finally, there appears to be a difference between the young and the old, and the midlife and the old but no difference between the young and the midlife. Older individuals are not able to respond to congestion as much as the other two age groups. This result may be explained by physical conditions that restrict their activities in the evening.

Marginal Cost of Congestion

The literature commonly attempts to measure the incremental cost of congestion because it provides a mechanism for determining the efficient tax or toll that should be implemented to alleviate congestion. Generally, it is measured in dollars per minute lost sitting in traffic or rather the value of travel time savings from avoiding congestion. The marginal cost of congestion is measured as the dollars per unit of congestion holding utility constant for a given choice alternative:

$$(4.8) \quad \frac{\partial w_n}{\partial c_{ni}} - \frac{\partial V_{ni} / \partial c_{ni}}{\partial V_{ni} / \partial w_n} = \frac{\beta_c + \beta_{kid} kids + \beta_{age} age + \beta_{wage} wage + \beta_{sex} sex + \beta_{car} car}{\beta_{wage} congestion}.$$

The marginal costs for the same groups of individuals are described in Table 4.12. For individuals with high opportunity costs of time, the cost of one additional car on the road would be approximately \$.01 as opposed to less than a penny for individuals with low opportunity costs of time. An additional car on the road for individuals with no children implies a marginal cost approximately equal to \$.05 as opposed to individuals with children where the marginal cost of congestion is actually negative. This again signifies these individuals have very little scheduling flexibility.

In most instances, the marginal costs of congestion are described in terms of the value of lost time. Because these additional cars are expected to affect travel time, it would seem appropriate to measure how one additional car impacts the time required to complete a trip. This would result in a measure of the dollars per minute as opposed to a measure of dollars per car. The conversion process used follows from a modification of

my earlier work (2004) where I create a broad rule of converting additional cars to their impact on travel time.

Table 4.12 The marginal cost of congestion⁹⁷

Demographic Group	Marginal Cost of Congestion
High Wage	\$.0127/car (0.00273)
Low Wage	\$.0090/car (0.0037)
No Children	\$.0511/car (0.0078)
At Least One Child	\$ -0.013/car (0.0117)
Young Age < 35 yrs old	\$.0413/car (0.00204)
Medium Age B/W 35 & 60	\$.0052/car (.00110)
Old Age >60 yrs old	\$.1241/car (0.0445)

The conversion process is outlined in the following steps:

- 1) In 1994, the average annualized daily traffic count in Wake County increased by 794 cars.⁹⁸ These additional cars are assumed to be distributed temporally throughout the day according to the distribution described in column 2 of Table 4.13.⁹⁹ It is assumed that each new car takes one non-work trip per day.
- 2) The average distance from a residential location to the location of a non-work activity is approximately 5.25 miles.
- 3) The effect on speed is determined by dividing the number of cars in each time period (column 3 in Table 4.13) by 5.25 miles. This gives a temporal measure of cars per mile of road.

⁹⁷ Standard errors are in parentheses below the coefficients and were calculated using the same bootstrapping methodology.

⁹⁸ This information was calculated from the North Carolina Department of Transportation traffic count data.

⁹⁹ This is the average distribution of cars over the eight intersections earlier described in Table 4.6.

- 4) For every additional car per mile of road, speed falls by a minimum of .3mph.¹⁰⁰ The magnitude of the speed change depends on the characteristics of the road, i.e. posted speed limit and traffic signals.
- 5) The average individual drives 51.12 miles per day.¹⁰¹ These trip miles are distributed temporally as specified in the last column of Table 4.13.¹⁰²
- 6) Given the miles driven in each period, a measure of additional time required to travel is calculated.

Example: In the AM peak period, an individual drives on average 9.78 miles with an average speed of 43.6 mph.¹⁰³ It originally took 13.45 minutes to complete the trip. Now that there are 63 more cars on the road. Speed reduces by $\frac{63cars}{5.25miles} * .3mph = 3.6 \text{ mph}$. Now, it takes the individual, 14.67 minutes to complete the same trip. The change in total travel time is 1.22 minutes.

- 7) Using this result, a measure of \$/hour is created by multiplying the additional time by the marginal costs detailed in Table 4.12 multiplied by 60 minutes. These \$/hour measures for each group of individuals are described in Table 4.14.¹⁰⁴

As a result, the incremental cost of an additional car converted to time ranges from \$.22 to \$1.24 per hour for individuals with high opportunity costs of time and for individuals with low opportunity costs of time the range is only \$.16 to \$1.24 per hour. In addition, the range for individuals with no children is between \$.89 and \$7.01 and for individuals with at least one child the range is actually negative. This cost is at its highest during the PM peak periods for all groups of individuals.

¹⁰⁰ The Center for Transportation Research and Education reports that the speed on the roadway reduces by .3mph for every additional vehicle on that road per mile of road.

¹⁰¹ The information on the average mileage of the trip was not available from the TTA survey. The information was collected from the National Personal Transportation Survey in 1995 that covered several areas of the United States.

¹⁰² Using the distribution of trips from the TTA data.

¹⁰³ The average speed limit in Wake County is 43.6 mph. This speed limit will be used for all computations.

¹⁰⁴ The intermediate steps of the conversion process are described in full detail in Table E11 in Appendix E.

Table 4.13 The distribution of cars and miles traveled throughout a day¹⁰⁵

Time Period	Percentage of cars per hour	# of Additional Cars Per hour	% of miles driven throughout day	# of miles driven during time period
AM peak	0.0793	63	19.13%	9.78
Off Peak	0.0664	53	20.13%	10.29
Lunch	0.07463	59	5.02%	2.57
PM peak	0.0998	79	28.19%	14.41
Evening	0.0452	36	27.0%	14.16

Table 4.14 The marginal cost of congestion, dollars per hour

Marginal Cost \$/Hour, Lower Bound							
Demographic Group	High Wage	Low Wage	No Children	At Least One Child	Young	Midlife	Old
AM	\$0.90	\$0.65	\$3.70	\$-0.94	\$2.99	\$0.36	\$1.64
Off Peak	\$0.79	\$0.57	\$3.24	\$-0.83	\$2.63	\$0.32	\$1.44
Lunch	\$0.22	\$0.16	\$0.89	\$-0.23	\$0.72	\$0.01	\$0.39
PM	\$1.24	\$1.24	\$7.01	\$-1.79	\$5.67	\$0.69	\$3.11
Evening	\$0.73	\$0.52	\$2.97	\$-0.76	\$2.40	\$0.29	\$1.31

4.8 Conclusion

The results from this study suggest that the decisions made translating non-work trips into a set of choice alternatives are important to efforts to measure the role of congestion for trip choices. The role of household features as influences to the effect of congestion on trip taking decisions becomes clear when the choices associated with the trip include both the timing as well as the purpose of the trip. When the choice of a trip is limited to one dimension, congestion and other household attributes that are hypothesized to be important factors in the choice of a trip are not significant. Once the choice set is

¹⁰⁵ This assumes an additional 794 cars daily.

expanded to other dimensions, an individual's ability to adapt to congestion appears to be limited by household circumstances.

This study finds clear evidence that household circumstances that constrain scheduling flexibility limit an individual's ability to adapt to congestion. Congestion deters individuals from making trips. However, the magnitude of an individual's sensitivity to congestion is influenced by an individual's constraints. These can include requirements that arise from household needs. For example, the presence of children reduces scheduling flexibility and implies individuals in these households may well be less able to respond to congestion. Individuals with higher wages will be more responsive to congestion because they sacrifice more, in terms of money, when time is wasted in traffic. Past work relies on the response to congestion by measuring the opportunity cost of time. Until now analysts have ignored the constraints of household factors on an individual's scheduling flexibility. This inevitably limits the trade between time and money.

Congestion management strategies have largely focused on work trips. This research provides evidence that household's non-work trip making behavior will also be influenced by congestion. Policies aimed to alleviate the congestion associated with work trips should consider that there is a relationship between an individual's work and non-work trip behavior. Most non-work trips occur during the morning and evening peak periods on the way to and from work. A policy that hinders individuals from accessing non-work locations as a segment of the work trip is likely to be unsuccessful. For example, a mass transit system is constructed to alleviate work related congestion.

However, the transit line is inaccessible to grocery stores, day care, and other essential non-work locations. Unless commercial development around the transit system emerges, individuals are unlikely to abandon the convenience of their personal automobiles.

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Appendix A

Table A1 Hedonic Results Dependent Variable = $\ln(\text{house price})$ ¹⁰⁶

Variable	Coefficient	t-statistic	Pr > t
Intercept	10.04345	174.82	<.0001
Year Built	0.000399	13.97	<.0001
Garage	0.000432	77.84	<.0001
Fireplace	0.0915	29.81	<.0001
Baths	0.04061	21.5	<.0001
Sqft	0.000366	168.99	<.0001
Mls1	0.2502	20.16	<.0001
Mls2	0.0151	1.38	0.1675
Mls3	-0.15253	-12.44	<.0001
Mls4	-0.00767	-0.66	0.512
Mls5	0.03548	3.24	0.0012
Mls6	-0.09053	-7.7	<.0001
Mls7	0.02046	1.77	0.0762
Mls8	-0.00982	-0.89	0.374
Mls9	0.05526	4.74	<.0001
Mls10	0.08083	7.04	<.0001
Mls11	-0.02177	-1.81	0.0701
Mls12	-0.11046	-7.41	<.0001
Mls13	-0.14833	-9.43	<.0001
Mls14	0.00955	0.8	0.4209
Mls15	0.0312	2.64	0.0084
Mls16	-0.04747	-3.66	0.0003
Mls17	-0.02493	-1.14	0.2529
Mls18	-0.00976	-0.71	0.4794
R square = .8084			

The results from the hedonic in Table A1 are consistent with the general hypotheses regarding the influences of housing structure on housing prices. As would be expected, bathrooms, square footage, and the existence of a garage or fireplace all have a positive influence on housing prices. Fixed effects specified for MLS zones were included. MLS zone 21 is the normalizing factor. Most of the fixed effects are highly significant. The results are also consistent with highlighting those areas in Wake County that are generally considered to have high housing values, i.e. Cary, Holly Springs, Northern

¹⁰⁶ Multiple Lists Sales zone 21 is the normalizing zone.

downtown Raleigh, and North Raleigh, MLS zones, 10, 9, 1, and 14 respectively. The housing price index used for the current study is constructed by taking the exponentials of the MLS coefficients, where the housing price index in MLS zone 21 is equal to one.

Appendix B

Following from Bell and Bockstael's (2000) hedonic price application, the GME estimator is based on the three moments of the error term, u , which appear in (B1 – B3).

$$(B1) \quad E\left[\frac{1}{N}u'u\right] = \sigma^2,$$

$$(B2) \quad E\left[\frac{1}{N}u'W'Wu\right] = \sigma^2 N^{-1}Tr(W'W), \text{ and}$$

$$(B3) \quad E\left[\frac{1}{N}u'W'u\right] = 0.$$

Rewriting the above moment conditions in terms of ε yields:

$$(B4) \quad E\left[\frac{1}{N}\varepsilon'(I - \rho W)'(I - \rho W)\varepsilon\right] = \sigma^2$$

$$(B5) \quad E\left[\frac{1}{N}\varepsilon'(I - \rho W)'W'W(I - \rho W)\varepsilon\right] = \frac{\sigma^2}{N}Tr(W'W)$$

$$(B6) \quad E\left[\frac{1}{N}\varepsilon'(I - \rho W)'W'(I - \rho W)\varepsilon\right] = 0$$

Consider the following three equation system implied the moments in terms of predictors for ε . The system is:

$$(B7) \quad G_N * [\rho, \rho^2, \sigma^2]' - g_N = v_N(\rho, \sigma^2)$$

where

$$(B8) \quad G_N = \begin{bmatrix} \frac{2}{N} \hat{\varepsilon}' \hat{\varepsilon} & \frac{-1}{N} \hat{\varepsilon}' \hat{\varepsilon} & 1 \\ \frac{2}{N} \hat{\varepsilon}' \hat{\varepsilon} & \frac{1}{N} \hat{\varepsilon}' \hat{\varepsilon} & \frac{1}{N} tr(W'W) \\ \frac{1}{N} (\hat{\varepsilon}' \hat{\varepsilon} + \hat{\varepsilon}' \hat{\varepsilon}) & \frac{-1}{N} \hat{\varepsilon}' \hat{\varepsilon} & 0 \end{bmatrix}^{107},$$

(B9)

G_N is a 3×3 matrix containing functions of $\hat{\varepsilon}$, predictors for ε , and elements of W ;

$\hat{\rho}$ and $\hat{\sigma}^2$ are defined as the minimizers of

$$(B10) \quad \left[\begin{array}{c} g_n - G_n \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_\varepsilon^2 \end{bmatrix} \end{array} \right]' \left[\begin{array}{c} g_n - G_n \begin{bmatrix} \rho \\ \rho^2 \\ \sigma_\varepsilon^2 \end{bmatrix} \end{array} \right].$$

¹⁰⁷ For presentation purposes, the notation is simplified: $\hat{\varepsilon} = W\varepsilon$ and $\ddot{\varepsilon} = WW\varepsilon$

Appendix C

The first step of Kelejian and Prucha's (1998) spatial autocorrelation estimator in the presence of endogenous right hand side variables is to compute the 2SLS with the selected instruments.

$$(C1) \quad \tilde{\delta}_n = (\hat{Z}_n^T \hat{Z}_n)^{-1} \hat{Z}_n^T y_n.$$

where $\hat{Z}_n = H_n (H_n^T H_n)^{-1} H_n^T X_n$, and H_n are a $n \times p$ set of instruments and X_n are the $n \times k$ set of exogenous regressors with $p > k$.

The second step uses residuals obtained from the two stage least squares estimation (C1) and then estimates the spatial autoregressive parameter with generalized moments estimation (GME). The final step re-estimates the regression by 2SLS by transforming the model using a method described below to account for spatial autocorrelation.

This step assumes that ρ is not known but has been estimated so that $\hat{\rho}$ replaces ρ in the final estimation step. The equation for the third step coefficient $\hat{\delta}_n$ is:

$$(C2) \quad \hat{\delta}_n = [\hat{Z}_{n*}(\hat{\rho}_n)^T \hat{Z}_{n*}(\hat{\rho}_n)]^{-1} \hat{Z}_{n*}(\hat{\rho}_n)^T y_{n*}(\hat{\rho}_n)$$

with $\hat{Z}_{n*}(\hat{\rho}_n) = (H_n (H_n^T H_n)^{-1} H_n^T)(X_n - \hat{\rho}_n W_n X_n)$ and $y_{n*} = y_n - \hat{\rho}_n W_n y_n$.

The asymptotic variance covariance matrix associated with $\hat{\delta}_n$ is:

$$(C3) \quad \hat{\sigma}_{\varepsilon,n}^2 [\hat{Z}_{n*}(\hat{\rho}_n)^T \hat{Z}_{n*}(\hat{\rho}_n)]^{-1}$$

where $\hat{\sigma}_{\varepsilon,n}^2 = (\hat{\varepsilon}_n^T \hat{\varepsilon}_n) / n$ with $\hat{\varepsilon}_n = y_{n*} - (X_n - \hat{\rho}_n W_n X_n) \hat{\delta}_n$.

Appendix D

**Table D1 Spatial Two Stage Least Squares Results, Dependent Variable = log(house price),
Congestion = Vehicle Count/Surface Width of Road¹⁰⁸**

	Inverse Distance Weight Matrix		Row Standardized Ones Weight Matrix	
	Cutoff = 200 m	Cutoff = 400 m	Cutoff = 200 m	Cutoff = 400 m
Variables				
Constant	11.0752 (172.31)	10.9603 (158.28)	11.0750 (171.97)	10.9604 (157.88)
Age of house	0.00430 (1.56)	-0.0021 (-0.72)	0.0046 (1.63)	-0.0020 (-0.77)
Baths	0.1840 (93.72)	0.1751 (89.48)	0.1836 (93.62)	0.1743 (89.23)
Fireplace	0.0007 (116.75)	0.0007 (112.78)	0.0007 (116.99)	0.0007 (113.65)
Garage	0.1382 (40.62)	0.1322 (39.25)	0.1384 (40.72)	0.1324 (39.42)
Area	0.0334 (49.96)	0.0326 (47.57)	0.0334 (50.06)	0.0327 (47.82)
Square Area	-0.0013 (-5.01)	-0.0010 (-4.18)	-0.0013 (-4.95)	-0.0010 (-4.15)
Sold in 1993	0.0311 (6.92)	0.0331 (7.67)	0.0312 (6.93)	0.0327 (7.56)
Sold in 1994	0.1088 (24.61)	0.1097 (25.94)	0.1088 (24.61)	0.1094 (25.77)
Sold in 1995	0.2040 (44.82)	0.2043 (46.83)	0.2042 (44.85)	0.2047 (46.74)
Sold in 1996	0.2366 (52.77)	0.2368 (54.98)	0.2365 (52.73)	0.2371 (54.84)
Sold in 1997	0.2740 (62.10)	0.2735 (64.45)	0.2739 (62.05)	0.2734 (64.19)
Sold in 1998	0.3100 (71.18)	0.3091 (73.63)	0.3099 (71.17)	0.3091 (73.39)
Sold in 1999	0.3476 (73.52)	0.3448 (76.08)	0.3476 (73.50)	0.3446 (75.81)
Age in census tract	-0.0065 (-17.97)	-0.0071 (-14.17)	-0.0065 (-17.81)	-0.0071 (-13.75)
Income in census tract	0.6443 (25.44)	0.6895 (19.68)	0.6451 (25.20)	0.6883 (19.07)
% white in census tract	-0.1184 (-1.80)	0.0305 (0.43)	-0.1194 (-1.82)	0.0300 (0.42)
% black in census tract	-0.1420 (-2.19)	0.0120 (0.17)	-0.1434 (-2.203)	0.0104 (0.15)
Miles to Research Park	-0.0088 (-27.20)	-0.0089 (-20.70)	-0.0087 (-26.85)	-0.0088 (-20.07)
Miles to downtown	0.0027 (4.57)	0.0038 (4.81)	0.0028 (4.60)	0.0040 (4.90)
Average daily vehicle/lane	-0.0002 (-2.93)	-0.0002 (-2.43)	-0.0002 (-2.90)	-0.0002 (-2.43)
Spatial Autocorrelation Parameter	$\rho = 0.4474$	$\rho = 0.6082$	$\rho = 0.4543$	$\rho = 0.6213$

¹⁰⁸ T-statistics are in parentheses below estimates.

**Table D2 Spatial Two Stage Least Squares -- Dependent Variable = log(house price),
Congestion variable = Commute Time¹⁰⁹**

	Inverse Distance Weight Matrix		Row Standardized Ones Weight Matrix	
	Cutoff = 200 m	Cutoff = 400 m	Cutoff = 200 m	Cutoff = 400 m
<u>Variables</u>				
Constant	10.8162 (114.73)	10.6053 (95.50)	10.8129 (13.92)	10.5839 (93.58)
Age of house	-0.0016 (-0.49)	-0.0087 (-2.65)	-0.0014 (-0.44)	-0.0092 (-2.77)
Baths	0.1784 (68.79)	0.1681 (62.92)	0.178 (68.61)	0.167 (62.35)
Fireplace	0.0007 (102.51)	0.0007 (94.86)	0.0007 (102.66)	0.0007 (94.97)
Garage	0.1335 (36.92)	0.1265 (34.47)	0.1337 (36.97)	0.1264 (34.38)
Area	0.0352 (40.89)	0.0347 (38.90)	0.0352 (40.91)	0.035 (38.81)
Square Area	-0.0014 (-5.46)	-0.0012 (-4.76)	-0.0014 (-5.41)	-0.0012 (-4.79)
Sold in 1993	0.0281 (6.14)	0.0291 (6.53)	0.0282 (6.15)	0.0285 (6.35)
Sold in 1994	0.1083 (24.36)	0.1088 (25.38)	0.1083 (24.36)	0.1084 (25.13)
Sold in 1995	0.2018 (43.75)	0.2016 (45.14)	0.2019 (43.78)	0.2017 (44.85)
Sold in 1996	0.2316 (49.57)	0.2307 (50.47)	0.2316 (49.51)	0.2307 (50.03)
Sold in 1997	0.2701 (59.54)	0.2686 (60.62)	0.2699 (59.46)	0.2681 (60.07)
Sold in 1998	0.3058 (67.52)	0.3042 (69.10)	0.3057 (67.48)	0.3039 (68.60)
Sold in 1999	0.3443 (71.77)	0.3408 (73.34)	0.3443 (71.75)	0.3404 (72.81)
Age in census tract	-0.0027 (-2.60)	-0.011 (-0.75)	-0.0026 (-2.51)	-0.0006 (-0.39)
Income in census tract	0.6664 (23.38)	0.7392 (18.78)	0.6677 (23.24)	0.7439 (18.24)
% white in census tract	0.1265 (1.26)	0.3757 (3.11)	0.1295 (1.26)	-0.398 (3.23)
% black in census tract	0.0672 (0.72)	0.3015 (2.77)	0.0692 (0.73)	0.3184 (2.88)
Miles to Research Park	-0.0093 (-24.03)	-0.0098 (-18.52)	-0.0093 (-23.73)	-0.0099 (-17.96)
Miles to downtown	0.0073 (6.34)	0.0107 (6.59)	0.0074 (6.36)	0.0113 (6.74)
Commute time	-0.0052 (-3.22)	-0.0085 (-3.70)	-0.0053 (-3.24)	-0.0093 (-3.84)
Spatial Autocorrelation Parameter	$\rho = 0.4462$	$\rho = 0.6169$	$\rho = 0.4641$	$\rho = 0.63$

¹⁰⁹ T-statistics are in parentheses below estimates

**Table D3 Spatial Two Stage Least Squares Results, Dependent variable = log(house price),
Congestion variable = levels (quintiles)¹¹⁰**

	Inverse Distance Weight Matrix		Row Standardized Ones Weight Matrix	
	Cutoff = 200 m	Cutoff = 400 m	Cutoff = 200 m	Cutoff = 400 m
Variables				
Constant	10.9908 (98.22)	10.8288 (85.65)	10.9919 (97.95)	10.8223 (86.32)
Age of house	-0.0045 (-0.94)	-0.0118 (-2.33)	-0.0041 (-0.86)	-0.0119 (-2.35)
Baths	0.2022 (82.02)	0.1908 (74.71)	0.2019 (82.08)	0.1900 (75.27)
Fireplace	0.0007 (95.89)	0.0007 (87.22)	0.0007 (95.98)	0.0007 (88.67)
Garage	0.0814 (0.32)	0.1456 (0.54)	0.07780 (0.3025)	0.1339 (0.49)
Area	0.0365 (43.38)	0.0348 (38.35)	0.0365 (43.37)	0.0349 (38.67)
Square Area	-0.0013 (-4.186)	-0.0010 (-3.00)	-0.0013 (-4.10)	-0.0010 (-2.99)
Sold in 1993	0.0246 (4.46)	0.0283 (4.99)	0.0245 (4.43)	0.028 (4.92)
Sold in 1994	0.0997 (18.04)	0.1014 (17.91)	0.0993 (17.90)	0.1013 (17.84)
Sold in 1995	0.1903 (29.49)	0.1913 (27.56)	0.1902 (29.27)	0.1920 (27.32)
Sold in 1996	0.2179 (36.01)	0.2169 (34.26)	0.2175 (35.68)	0.2175 (34.13)
Sold in 1997	0.2604 (45.31)	0.2592 (43.39)	0.2599 (44.88)	0.2589 (42.94)
Sold in 1998	0.2971 (52.17)	0.2968 (49.98)	0.2965 (51.71)	0.2970 (49.64)
Sold in 1999	0.3373 (57.28)	0.3344 (56.43)	0.3369 (56.91)	0.3337 (56.04)
Age in census tract	-0.0045 (-8.72)	-0.0047 (-6.39)	-0.0045 (-8.60)	-0.0048 (-6.36)
Income in census tract	0.5517 (16.54)	0.5847 (12.19)	0.5509 (16.38)	0.5873 (12.01)
% white in census tract	-0.0838 (-0.65)	0.0012 (0.01)	-0.0864 (-0.656)	-0.017 (-0.0842)
% black in census tract	-0.1221 (-0.95)	-0.345 (-0.17)	-0.1280 (-0.98)	-0.0535 (-0.22)
Miles to Research Park	-0.0123 (-14.19)	-0.0126 (-10.91)	-0.0123 (-13.880)	-0.0124 (-10.64)
Miles to downtown	0.077 (8.81)	0.0097 (7.68)	0.0078 (8.78)	0.0100 (7.77)
First level congestion	-0.001 (-0.68)	-0.0004 (-0.15)	-0.0010 (-0.65)	-0.0001 (-0.14)
Second level congestion	0.0017 (1.97)	0.0023 (1.83)	0.0017 (1.95)	0.0024 (1.82)
Third level congestion	0.0003 (0.61)	0.0007 (1.08)	0.0003 (0.59)	0.0008 (1.18)
Fourth level congestion	0.0000 (0.12)	0.0000 (0.06)	0.0000 (0.09)	0.0001 (0.11)
Fifth level congestion	0.0002 (0.94)	0.0003 (1.12)	0.0002 (0.94)	0.0003 (1.18)
Spatial Autocorrelation Parameter	$\rho = 0.4696$	$\rho = 0.6300$	$\rho = 0.4761$	$\rho = 0.6424$

¹¹⁰ T-statistics are in parentheses below estimates.

Appendix E

Table E1 Choice: Activity, Each Time Period Tested Separately (Meals = Normalizing Choice)¹¹¹

	Model				
	Am Peak 535 obs	Off Peak 572 obs	Lunch 142 obs	Pm Peak 787 obs	Evening 775 obs
Distance	.00006168 (1.564)	0.000017 (0.620)	-0.000033 (-0.368)	0.0000049 (0.191)	-0.000004 (-0.158)
Private					
Constant	1.073* (2.197)	-0.5547 (-1.080)	-2.465* (-2.099)	-2.034* (-4.179)	-1.352* (-2.713)
Congestion	.0000194 (.154)	-0.000127 (-1.058)	-.000094 (-0.337)	-0.000012 (-0.151)	-0.000194 (-1.169)
# Cars/ Driver	-.5889* (-3.049)	-0.2071 (-0.860)	-0.8233 (-1.276)	0.1763 (0.847)	0-0.2172 (-0.989)
# Kids	.6382* (5.126)	0.2727* (2.515)	0.2723 (1.200)	0.1398 (1.553)	0.4318* (4.379)
Age	-.00652 (-0.834)	0.01571 (1.772)	0.003322 (1.811)	0.00882 (1.089)	0.0195* (2.024)
Gender	.02063 (0.798)	0.00999 (0.039)	-0.1048 (-0.206)	-0.06061 (-0.294)	0.0153 (0.068)
Wage/Driver	.00597* (2.288)	0.002828 (1.135)	0.005481 (1.080)	0.00210 (1.051)	-0.003599 (-1.543)
Amusements					
Constant	-0.9991 (-1.265)	-0.8378 (-1.578)	-5.157 (-3.119)	-0.6368 (-1.549)	-0.2736 (-0.758)
Congestion	0.000190 (1.032)	-0.000175 (-1.383)	0.000251 (0.760)	0.000104 (1.492)	0.0000454 (0.377)
# Cars/ Driver	-0.5252 (-1.544)	0.3620 (1.535)	1.010 (1.436)	0.1436 (0.769)	-0.4547* (-2.775)
# Kids	0.20177 (1.027)	0.3979* (3.538)	0.2991 (1.079)	-0.03425 (-0.409)	0.01859 (0.228)
Age	-0.00342 (-0.268)	0.002707 (0.287)	0.04268 (1.887)	-0.01417 (-1.830)	0.01687* (2.306)
Gender	-0.2488 (-0.591)	0.02042 (0.77)	1.394* (2.019)	-0.1279 (-0.665)	0.1565 (0.908)
Wage/Driver	0.005374 (1.355)	0.00103 (0.391)	-0.0145 (-1.593)	0.00048 (0.251)	0.000385 (0.255)
Shopping					
Constant	-0.9651 (-1.361)	-1.091 (-1.941)	-3.535* (-2.395)	-2.327* (-4.305)	-1.469* (-2.954)
Congestion	0.000031 (.168)	-0.000191 (-1.378)	-0.000204 (-0.586)	0.000044 (0.490)	0.000413* (2.718)
# Cars/ Driver	-0.3735 (-1.426)	-0.3226 (-1.219)	-0.6054 (-0.759)	0.1383 (0.582)	0.07752 (0.408)
# Kids	-0.1713 (-0.862)	-0.08599 (-0.689)	0.4813 (1.910)	0.003867 (0.037)	0.03353 (0.297)
Age	0.009715 (0.882)	0.0334* (3.624)	0.03599 (1.649)	0.00947 (1.070)	-0.007616 (-0.705)
Gender	-0.2339 (-0.619)	0.2653 (0.993)	0.9046 (1.536)	0.03554 (0.154)	-0.0995 (-0.410)
Wage/Driver	0.00453 (1.270)	0.001646 (0.616)	0.002944 (0.464)	0.00244 (1.094)	0.002067 (1.103)

¹¹¹ Significant parameters are noted with an asterisk, t-statistics are in parentheses below the coefficients.

Table E2 Choice: Departure Time, Each Activity Tested Separately (Evening= Normalizing Choice)¹¹²

	Personal Business 803 obs	Amusements 633 obs	Shopping 382 obs	Meals 993 obs
Congestion	-0.000237 (-0.452)	-0.0001084 (-2.62)	-0.00207 (-2.852)	-0.00504 (-1.627)
Congest*wage	0.0000102 (0.526)	-0.0000084 (-0.5390)	-0.000024 (-1.129)	-0.000012 (-0.828)
Congest*gender	-0.000199 (-0.843)	0.0000037 (0.020)	0.000627 (2.239)	0.000179 (1.206)
Congest*age	0.0000037 (0.411)	-0.0000034 (-0.423)	-0.000025 (-2.370)	0.000013 (2.148)
Congest*#kids	-0.000079 (-0.793)	0.000129 (1.676)	0.000329 (2.501)	0.00019 (2.978)
Congest*cars	0.000235 (0.960)	0.000126 (0.974)	-0.000039 (-0.141)	-0.00021 (-1.329)
ASC AM PEAK	1.086 (8.743)	-2.059 (-10.87)	-0.302 (-1.444)	-1.134 (-8.630)
ASC OFFPEAK	0.32065 (2.489)	-0.6312 (-5.697)	0.5723 (3.615)	-0.7388 (-6.664)
ASC LUNCH	-1.722 (-7.147)	-3.13 (-10.416)	-1.489 (-5.026)	-1.0615 (-8.339)
ASC PM PEAK	-0.02173 (-0.117)	-0.5095 (-3.272)	0.6601 (2.756)	0.44157 (3.737)

¹¹² Significant results are in bold and t-statistics are in parentheses below the coefficients.

Table E3 Marginal Effect of Congestion for Individuals with Low Wages, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal (rows)

-1.9E-06	1.3E-07	1.0E-07	-4.4E-08	2.2E-07	9.2E-08	1.3E-07	1.0E-07	-4.6E-08	2.3E-07	8.9E-08	1.3E-07	9.7E-08	-4.6E-08	2.3E-07	9.2E-08	1.3E-07	1.0E-07	-5.1E-08	2.3E-07
1.3E-07	-2.8E-06	1.5E-07	-3.4E-09	2.7E-07	1.4E-07	1.8E-07	1.5E-07	-4.8E-09	2.8E-07	1.4E-07	1.8E-07	1.4E-07	-3.3E-09	2.8E-07	1.4E-07	1.7E-07	1.5E-07	-7.1E-09	2.8E-07
1.0E-07	1.5E-07	-2.1E-06	-3.7E-08	2.3E-07	1.0E-07	1.5E-07	1.2E-07	-3.9E-08	2.5E-07	9.9E-08	1.5E-07	1.1E-07	-3.9E-08	2.5E-07	1.0E-07	1.4E-07	1.2E-07	-4.6E-08	2.4E-07
-4.4E-08	-3.4E-09	-3.7E-08	6.3E-07	7.3E-08	-4.4E-08	-6.8E-09	-3.1E-08	-1.9E-07	7.7E-08	-4.8E-08	-2.1E-09	-3.3E-08	-2.0E-07	7.5E-08	-4.2E-08	-4.7E-09	-3.3E-08	-2.1E-07	7.7E-08
2.2E-07	2.7E-07	2.3E-07	7.3E-08	-4.3E-06	2.2E-07	2.7E-07	2.3E-07	7.2E-08	3.9E-07	2.2E-07	2.7E-07	2.2E-07	7.7E-08	4.0E-07	2.2E-07	2.6E-07	2.3E-07	7.4E-08	3.9E-07
9.2E-08	1.4E-07	1.0E-07	-4.4E-08	2.2E-07	-2.0E-06	1.4E-07	1.1E-07	-4.6E-08	2.3E-07	9.2E-08	1.4E-07	1.0E-07	-4.7E-08	2.3E-07	9.4E-08	1.3E-07	1.1E-07	-5.1E-08	2.3E-07
1.3E-07	1.8E-07	1.5E-07	-6.8E-09	2.7E-07	1.4E-07	-2.7E-06	1.5E-07	-8.6E-09	2.8E-07	1.3E-07	1.8E-07	1.4E-07	-7.1E-09	2.8E-07	1.3E-07	1.7E-07	1.5E-07	-1.4E-08	2.8E-07
1.0E-07	1.5E-07	1.2E-07	-3.1E-08	2.3E-07	1.1E-07	1.5E-07	-2.2E-06	-3.3E-08	2.4E-07	1.0E-07	1.5E-07	1.1E-07	-3.3E-08	2.4E-07	1.0E-07	1.4E-07	1.2E-07	-3.7E-08	2.4E-07
-4.6E-08	-4.8E-09	-3.9E-08	-1.9E-07	7.2E-08	-4.6E-08	-8.6E-09	-3.3E-08	6.5E-07	7.7E-08	-5.0E-08	-3.5E-09	-3.5E-08	-2.0E-07	7.4E-08	-4.4E-08	-6.5E-09	-3.5E-08	-2.1E-07	7.6E-08
2.3E-07	2.8E-07	2.5E-07	7.7E-08	3.9E-07	2.3E-07	2.8E-07	2.4E-07	7.7E-08	-4.5E-06	2.3E-07	2.8E-07	2.3E-07	8.2E-08	4.1E-07	2.3E-07	2.7E-07	2.5E-07	7.9E-08	4.0E-07
8.9E-08	1.4E-07	9.9E-08	-4.8E-08	2.2E-07	9.2E-08	1.3E-07	1.0E-07	-5.0E-08	2.3E-07	-1.9E-06	1.3E-07	9.7E-08	-5.1E-08	2.3E-07	9.1E-08	1.3E-07	1.0E-07	-5.8E-08	2.3E-07
1.3E-07	1.8E-07	1.5E-07	-2.1E-09	2.7E-07	1.4E-07	1.8E-07	1.5E-07	-3.5E-09	2.8E-07	1.3E-07	-2.7E-06	1.4E-07	-2.3E-09	2.8E-07	1.3E-07	1.7E-07	1.5E-07	-6.1E-09	2.7E-07
9.7E-08	1.4E-07	1.1E-07	-3.3E-08	2.2E-07	1.0E-07	1.4E-07	1.1E-07	-3.5E-08	2.3E-07	9.7E-08	1.4E-07	-2.1E-06	-3.5E-08	2.3E-07	9.8E-08	1.3E-07	1.1E-07	-3.9E-08	2.3E-07
-4.6E-08	-3.3E-09	-3.9E-08	-2.0E-07	7.7E-08	-4.7E-08	-7.1E-09	-3.3E-08	-2.0E-07	8.2E-08	-5.1E-08	-2.3E-09	-3.5E-08	6.5E-07	7.9E-08	-4.5E-08	-4.8E-09	-3.5E-08	-2.2E-07	8.1E-08
2.3E-07	2.8E-07	2.5E-07	7.5E-08	4.0E-07	2.3E-07	2.8E-07	2.4E-07	7.4E-08	4.1E-07	2.3E-07	2.8E-07	2.3E-07	7.9E-08	-4.5E-06	2.3E-07	2.7E-07	2.5E-07	7.4E-08	4.1E-07
9.2E-08	1.4E-07	1.0E-07	-4.2E-08	2.2E-07	9.4E-08	1.3E-07	1.0E-07	-4.4E-08	2.3E-07	9.1E-08	1.3E-07	9.8E-08	-4.5E-08	2.3E-07	-1.9E-06	1.3E-07	1.1E-07	-4.9E-08	2.3E-07
1.3E-07	1.7E-07	1.4E-07	-4.7E-09	2.6E-07	1.3E-07	1.7E-07	1.4E-07	-6.5E-09	2.7E-07	1.3E-07	1.7E-07	1.3E-07	-4.8E-09	2.7E-07	1.3E-07	-2.6E-06	1.4E-07	-8.6E-09	2.7E-07
1.0E-07	1.5E-07	1.2E-07	-3.3E-08	2.3E-07	1.1E-07	1.5E-07	1.2E-07	-3.5E-08	2.5E-07	1.0E-07	1.5E-07	1.1E-07	-3.5E-08	2.5E-07	1.1E-07	1.4E-07	-2.2E-06	-3.9E-08	2.4E-07
-5.1E-08	-7.1E-09	-4.6E-08	-2.1E-07	7.4E-08	-5.1E-08	-1.4E-08	-3.7E-08	-2.1E-07	7.9E-08	-5.8E-08	-6.1E-09	-3.9E-08	-2.2E-07	7.4E-08	-4.9E-08	-8.6E-09	-3.9E-08	7.3E-07	7.9E-08
2.3E-07	2.8E-07	2.4E-07	7.7E-08	3.9E-07	2.3E-07	2.8E-07	2.4E-07	7.6E-08	4.0E-07	2.3E-07	2.7E-07	2.3E-07	8.1E-08	4.1E-07	2.3E-07	2.7E-07	2.4E-07	7.9E-08	-4.5E-06

Table E4 Marginal Effect of Congestion for People with High Wages, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal (rows)

-4.8E-06	2.9E-07	2.5E-07	1.7E-07	2.9E-07	2.6E-07	2.7E-07	2.5E-07	1.5E-07	3.4E-07	2.5E-07	2.7E-07	2.2E-07	1.9E-07	3.3E-07	2.5E-07	2.4E-07	2.6E-07	1.7E-07	3.3E-07
2.9E-07	-5.8E-06	3.1E-07	2.3E-07	3.4E-07	3.3E-07	3.3E-07	3.1E-07	2.0E-07	4.0E-07	3.1E-07	3.3E-07	2.7E-07	2.6E-07	3.8E-07	3.1E-07	2.9E-07	3.3E-07	2.3E-07	3.8E-07
2.5E-07	3.1E-07	-5.1E-06	1.7E-07	3.1E-07	2.8E-07	3.0E-07	2.7E-07	1.6E-07	3.6E-07	2.7E-07	2.9E-07	2.3E-07	2.0E-07	3.6E-07	2.7E-07	2.6E-07	2.8E-07	1.9E-07	3.5E-07
1.7E-07	2.3E-07	1.7E-07	-3.5E-06	2.4E-07	2.0E-07	2.1E-07	1.9E-07	-4.0E-09	3.0E-07	1.8E-07	2.2E-07	1.5E-07	4.5E-08	2.8E-07	1.9E-07	1.8E-07	2.0E-07	8.6E-09	2.9E-07
2.9E-07	3.4E-07	3.1E-07	2.4E-07	-5.9E-06	3.2E-07	3.3E-07	3.1E-07	2.3E-07	4.0E-07	3.1E-07	3.2E-07	2.8E-07	2.7E-07	3.9E-07	3.1E-07	2.9E-07	3.2E-07	2.5E-07	3.9E-07
2.6E-07	3.3E-07	2.8E-07	2.0E-07	3.2E-07	-5.4E-06	3.1E-07	2.9E-07	1.7E-07	3.8E-07	2.8E-07	3.1E-07	2.5E-07	2.3E-07	3.6E-07	2.9E-07	2.7E-07	3.0E-07	2.0E-07	3.7E-07
2.7E-07	3.3E-07	3.0E-07	2.1E-07	3.3E-07	3.1E-07	-5.5E-06	2.9E-07	1.9E-07	3.8E-07	3.0E-07	3.1E-07	2.6E-07	2.3E-07	3.8E-07	2.9E-07	2.8E-07	3.0E-07	2.2E-07	3.7E-07
2.5E-07	3.1E-07	2.7E-07	1.9E-07	3.1E-07	2.9E-07	2.9E-07	-5.1E-06	1.6E-07	3.6E-07	2.7E-07	3.0E-07	2.4E-07	2.1E-07	3.5E-07	2.7E-07	2.6E-07	2.9E-07	1.9E-07	3.5E-07
1.5E-07	2.0E-07	1.6E-07	-4.0E-09	2.3E-07	1.7E-07	1.9E-07	1.6E-07	-3.0E-06	2.7E-07	1.6E-07	1.9E-07	1.4E-07	8.1E-09	2.6E-07	1.6E-07	1.7E-07	1.7E-07	-4.9E-09	2.6E-07
3.4E-07	4.0E-07	3.6E-07	3.0E-07	4.0E-07	3.8E-07	3.8E-07	3.6E-07	2.7E-07	-6.9E-06	3.6E-07	3.8E-07	3.2E-07	3.3E-07	4.6E-07	3.7E-07	3.4E-07	3.8E-07	3.0E-07	4.5E-07
2.5E-07	3.1E-07	2.7E-07	1.8E-07	3.1E-07	2.8E-07	3.0E-07	2.7E-07	1.6E-07	3.6E-07	-5.1E-06	2.9E-07	2.4E-07	2.0E-07	3.6E-07	2.7E-07	2.6E-07	2.8E-07	1.9E-07	3.5E-07
2.7E-07	3.3E-07	2.9E-07	2.2E-07	3.2E-07	3.1E-07	3.1E-07	3.0E-07	1.9E-07	3.8E-07	2.9E-07	-5.6E-06	2.6E-07	2.5E-07	3.7E-07	3.0E-07	2.8E-07	3.1E-07	2.2E-07	3.7E-07
2.2E-07	2.7E-07	2.3E-07	1.5E-07	2.8E-07	2.5E-07	2.6E-07	2.4E-07	1.4E-07	3.2E-07	2.4E-07	2.6E-07	-4.5E-06	1.7E-07	3.1E-07	2.4E-07	2.3E-07	2.5E-07	1.6E-07	3.1E-07
1.9E-07	2.6E-07	2.0E-07	4.5E-08	2.7E-07	2.3E-07	2.3E-07	2.1E-07	8.1E-09	3.3E-07	2.0E-07	2.5E-07	1.7E-07	-3.9E-06	3.0E-07	2.2E-07	2.0E-07	2.2E-07	2.5E-08	3.1E-07
3.3E-07	3.8E-07	3.6E-07	2.8E-07	3.9E-07	3.6E-07	3.8E-07	3.5E-07	2.6E-07	4.6E-07	3.6E-07	3.7E-07	3.1E-07	3.0E-07	-6.7E-06	3.5E-07	3.3E-07	3.6E-07	2.9E-07	4.4E-07
2.5E-07	3.1E-07	2.7E-07	1.9E-07	3.1E-07	2.9E-07	2.9E-07	2.7E-07	1.6E-07	3.7E-07	2.7E-07	3.0E-07	2.4E-07	2.2E-07	3.5E-07	-5.2E-06	2.6E-07	2.9E-07	1.9E-07	3.5E-07
2.4E-07	2.9E-07	2.6E-07	1.8E-07	2.9E-07	2.7E-07	2.8E-07	2.6E-07	1.7E-07	3.4E-07	2.6E-07	2.8E-07	2.3E-07	2.0E-07	3.3E-07	2.6E-07	-4.9E-06	2.7E-07	1.9E-07	3.3E-07
2.6E-07	3.3E-07	2.8E-07	2.0E-07	3.2E-07	3.0E-07	3.0E-07	2.9E-07	1.7E-07	3.8E-07	2.8E-07	3.1E-07	2.5E-07	2.2E-07	3.6E-07	2.9E-07	2.7E-07	-5.4E-06	2.0E-07	3.6E-07
1.7E-07	2.3E-07	1.9E-07	8.6E-09	2.5E-07	2.0E-07	2.2E-07	1.9E-07	-4.9E-09	3.0E-07	1.9E-07	2.2E-07	1.6E-07	2.5E-08	2.9E-07	1.9E-07	1.9E-07	2.0E-07	-3.5E-06	2.9E-07
3.3E-07	3.8E-07	3.5E-07	2.9E-07	3.9E-07	3.7E-07	3.7E-07	3.5E-07	2.6E-07	4.5E-07	3.5E-07	3.7E-07	3.1E-07	3.1E-07	4.4E-07	3.5E-07	3.3E-07	3.6E-07	2.9E-07	-6.6E-06

Table E5 Marginal Effect of Congestion for People with No Children, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal (rows)

-1.02E-05	5.6E-07	5.3E-07	4.6E-07	6.0E-07	5.4E-07	5.5E-07	5.4E-07	4.5E-07	6.2E-07	5.3E-07	5.6E-07	5.2E-07	4.7E-07	6.2E-07	5.3E-07	5.4E-07	5.4E-07	4.6E-07	6.2E-07
5.6E-07	-1.1E-05	5.7E-07	5.0E-07	6.5E-07	5.8E-07	5.9E-07	5.8E-07	4.8E-07	6.7E-07	5.7E-07	6.0E-07	5.6E-07	5.1E-07	6.6E-07	5.7E-07	5.8E-07	5.8E-07	5.0E-07	6.7E-07
5.3E-07	5.7E-07	-1.1E-05	4.7E-07	6.1E-07	5.5E-07	5.7E-07	5.5E-07	4.6E-07	6.4E-07	5.4E-07	5.7E-07	5.3E-07	4.8E-07	6.3E-07	5.4E-07	5.5E-07	5.6E-07	4.8E-07	6.3E-07
4.6E-07	5.0E-07	4.7E-07	-9.1E-06	5.1E-07	4.8E-07	4.9E-07	4.8E-07	4.1E-07	5.4E-07	4.7E-07	4.9E-07	4.6E-07	4.3E-07	5.3E-07	4.7E-07	4.7E-07	4.8E-07	4.2E-07	5.3E-07
6.0E-07	6.5E-07	6.1E-07	5.1E-07	-1.2E-05	6.2E-07	6.4E-07	6.1E-07	5.0E-07	7.5E-07	6.1E-07	6.4E-07	6.0E-07	5.2E-07	7.4E-07	6.1E-07	6.2E-07	6.2E-07	5.2E-07	7.5E-07
5.4E-07	5.8E-07	5.5E-07	4.8E-07	6.2E-07	-1.1E-05	5.7E-07	5.5E-07	4.6E-07	6.4E-07	5.4E-07	5.7E-07	5.3E-07	4.9E-07	6.3E-07	5.5E-07	5.5E-07	5.6E-07	4.8E-07	6.4E-07
5.5E-07	5.9E-07	5.7E-07	4.9E-07	6.4E-07	5.7E-07	-1.1E-05	5.7E-07	4.8E-07	6.6E-07	5.6E-07	5.9E-07	5.5E-07	5.0E-07	6.6E-07	5.6E-07	5.7E-07	5.7E-07	4.9E-07	6.6E-07
5.4E-07	5.8E-07	5.5E-07	4.8E-07	6.1E-07	5.5E-07	5.7E-07	-1.1E-05	4.7E-07	6.4E-07	5.4E-07	5.8E-07	5.4E-07	4.9E-07	6.3E-07	5.5E-07	5.5E-07	5.6E-07	4.8E-07	6.4E-07
4.5E-07	4.8E-07	4.6E-07	4.1E-07	5.0E-07	4.6E-07	4.8E-07	4.7E-07	-8.9E-06	5.2E-07	4.6E-07	4.8E-07	4.5E-07	4.2E-07	5.2E-07	4.6E-07	4.6E-07	4.7E-07	4.1E-07	5.2E-07
6.2E-07	6.7E-07	6.4E-07	5.4E-07	7.5E-07	6.4E-07	6.6E-07	6.4E-07	5.2E-07	-1.2E-05	6.3E-07	6.7E-07	6.2E-07	5.5E-07	7.7E-07	6.4E-07	6.5E-07	6.5E-07	5.4E-07	7.8E-07
5.3E-07	5.7E-07	5.4E-07	4.7E-07	6.1E-07	5.4E-07	5.6E-07	5.4E-07	4.6E-07	6.3E-07	-1.0E-05	5.6E-07	5.3E-07	4.8E-07	6.3E-07	5.4E-07	5.4E-07	5.5E-07	4.7E-07	6.3E-07
5.6E-07	6.0E-07	5.7E-07	4.9E-07	6.4E-07	5.7E-07	5.9E-07	5.8E-07	4.8E-07	6.7E-07	5.6E-07	-1.1E-05	5.5E-07	5.0E-07	6.6E-07	5.7E-07	5.7E-07	5.8E-07	4.9E-07	6.6E-07
5.2E-07	5.6E-07	5.3E-07	4.6E-07	6.0E-07	5.3E-07	5.5E-07	5.4E-07	4.5E-07	6.2E-07	5.3E-07	5.5E-07	-1.0E-05	4.7E-07	6.1E-07	5.3E-07	5.4E-07	5.4E-07	4.6E-07	6.1E-07
4.7E-07	5.1E-07	4.8E-07	4.3E-07	5.2E-07	4.9E-07	5.0E-07	4.9E-07	4.2E-07	5.5E-07	4.8E-07	5.0E-07	4.7E-07	-9.3E-06	5.4E-07	4.8E-07	4.8E-07	5.0E-07	4.3E-07	5.4E-07
6.2E-07	6.6E-07	6.3E-07	5.3E-07	7.4E-07	6.3E-07	6.6E-07	6.3E-07	5.2E-07	7.7E-07	6.3E-07	6.6E-07	6.1E-07	5.4E-07	-1.2E-05	6.3E-07	6.4E-07	6.4E-07	5.3E-07	7.7E-07
5.3E-07	5.7E-07	5.4E-07	4.7E-07	6.1E-07	5.5E-07	5.6E-07	5.5E-07	4.6E-07	6.4E-07	5.4E-07	5.7E-07	5.3E-07	4.8E-07	6.3E-07	-1.1E-05	5.5E-07	5.5E-07	4.7E-07	6.3E-07
5.4E-07	5.8E-07	5.5E-07	4.7E-07	6.2E-07	5.5E-07	5.7E-07	5.5E-07	4.6E-07	6.5E-07	5.4E-07	5.7E-07	5.4E-07	4.8E-07	6.4E-07	5.5E-07	-1.1E-05	5.6E-07	4.8E-07	6.4E-07
5.4E-07	5.8E-07	5.6E-07	4.8E-07	6.2E-07	5.6E-07	5.7E-07	5.6E-07	4.7E-07	6.5E-07	5.5E-07	5.8E-07	5.4E-07	5.0E-07	6.4E-07	5.5E-07	5.6E-07	-1.1E-05	4.8E-07	6.4E-07
4.6E-07	5.0E-07	4.8E-07	4.2E-07	5.2E-07	4.8E-07	4.9E-07	4.8E-07	4.1E-07	5.4E-07	4.7E-07	4.9E-07	4.6E-07	4.3E-07	5.3E-07	4.7E-07	4.8E-07	4.8E-07	-9.1E-06	5.3E-07
6.2E-07	6.7E-07	6.3E-07	5.3E-07	7.5E-07	6.4E-07	6.6E-07	6.4E-07	5.2E-07	7.8E-07	6.3E-07	6.6E-07	6.1E-07	5.4E-07	7.7E-07	6.3E-07	6.4E-07	6.4E-07	5.3E-07	-1.2E-05

Table E6 Marginal Effect of Congestion for People ≥ 1 child, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal

(rows)																				
4.92E-06	-2.1E-07	-2.7E-07	-4.1E-07	-1.3E-07	-2.6E-07	-2.3E-07	-2.5E-07	-4.1E-07	-1.3E-07	-2.9E-07	-2.2E-07	-2.3E-07	-4.4E-07	-1.5E-07	-2.7E-07	-2.0E-07	-2.4E-07	-4.6E-07	-1.3E-07	
-2.1E-07	4.0E-06	-2.2E-07	-3.5E-07	-8.6E-08	-2.1E-07	-1.9E-07	-2.0E-07	-3.4E-07	-8.6E-08	-2.3E-07	-1.7E-07	-1.9E-07	-3.7E-07	-1.1E-07	-2.1E-07	-1.6E-07	-2.0E-07	-3.9E-07	-9.1E-08	
-2.7E-07	-2.2E-07	5.1E-06	-4.1E-07	-1.3E-07	-2.7E-07	-2.5E-07	-2.6E-07	-4.0E-07	-1.4E-07	-3.0E-07	-2.2E-07	-2.4E-07	-4.4E-07	-1.7E-07	-2.7E-07	-2.1E-07	-2.5E-07	-4.7E-07	-1.4E-07	
-4.1E-07	-3.5E-07	-4.1E-07	7.8E-06	-2.3E-07	-4.3E-07	-3.7E-07	-3.9E-07	-6.7E-07	-2.4E-07	-4.4E-07	-3.5E-07	-3.7E-07	-7.4E-07	-2.6E-07	-4.2E-07	-3.2E-07	-3.9E-07	-7.4E-07	-2.4E-07	
-1.3E-07	-8.6E-08	-1.3E-07	-2.3E-07	2.4E-06	-1.2E-07	-1.1E-07	-1.2E-07	-2.2E-07	-1.9E-08	-1.4E-07	-9.1E-08	-1.1E-07	-2.4E-07	-3.8E-08	-1.3E-07	-8.4E-08	-1.1E-07	-2.6E-07	-2.5E-08	
-2.6E-07	-2.1E-07	-2.7E-07	-4.3E-07	-1.2E-07	5.0E-06	-2.3E-07	-2.5E-07	-4.2E-07	-1.3E-07	-2.9E-07	-2.1E-07	-2.3E-07	-4.5E-07	-1.5E-07	-2.7E-07	-2.0E-07	-2.4E-07	-4.7E-07	-1.3E-07	
-2.3E-07	-1.9E-07	-2.5E-07	-3.7E-07	-1.1E-07	-2.3E-07	4.5E-06	-2.2E-07	-3.6E-07	-1.1E-07	-2.7E-07	-1.9E-07	-2.1E-07	-3.9E-07	-1.4E-07	-2.4E-07	-1.8E-07	-2.2E-07	-4.2E-07	-1.2E-07	
-2.5E-07	-2.0E-07	-2.6E-07	-3.9E-07	-1.2E-07	-2.5E-07	-2.2E-07	4.7E-06	-3.8E-07	-1.2E-07	-2.7E-07	-2.0E-07	-2.2E-07	-4.1E-07	-1.4E-07	-2.5E-07	-1.9E-07	-2.3E-07	-4.4E-07	-1.2E-07	
-4.1E-07	-3.4E-07	-4.0E-07	-6.7E-07	-2.2E-07	-4.2E-07	-3.6E-07	-3.8E-07	7.6E-06	-2.4E-07	-4.3E-07	-3.4E-07	-3.6E-07	-7.2E-07	-2.6E-07	-4.1E-07	-3.2E-07	-3.9E-07	-7.2E-07	-2.4E-07	
-1.3E-07	-8.6E-08	-1.4E-07	-2.4E-07	-1.9E-08	-1.3E-07	-1.1E-07	-1.2E-07	-2.4E-07	2.4E-06	-1.5E-07	-9.1E-08	-1.1E-07	-2.6E-07	-2.3E-08	-1.3E-07	-8.4E-08	-1.1E-07	-2.8E-07	-9.6E-09	
-2.9E-07	-2.3E-07	-3.0E-07	-4.4E-07	-1.4E-07	-2.9E-07	-2.7E-07	-2.7E-07	-4.3E-07	-1.5E-07	5.4E-06	-2.4E-07	-2.5E-07	-4.7E-07	-1.8E-07	-2.9E-07	-2.2E-07	-2.7E-07	-5.0E-07	-1.5E-07	
-2.2E-07	-1.7E-07	-2.2E-07	-3.5E-07	-9.1E-08	-2.1E-07	-1.9E-07	-2.0E-07	-3.4E-07	-9.1E-08	-2.4E-07	4.1E-06	-1.9E-07	-3.7E-07	-1.2E-07	-2.2E-07	-1.6E-07	-2.0E-07	-3.9E-07	-9.7E-08	
-2.3E-07	-1.9E-07	-2.4E-07	-3.7E-07	-1.1E-07	-2.3E-07	-2.1E-07	-2.2E-07	-3.6E-07	-1.1E-07	-2.5E-07	-1.9E-07	4.4E-06	-3.9E-07	-1.3E-07	-2.3E-07	-1.8E-07	-2.2E-07	-4.0E-07	-1.1E-07	
-4.4E-07	-3.7E-07	-4.4E-07	-7.4E-07	-2.4E-07	-4.5E-07	-3.9E-07	-4.1E-07	-7.2E-07	-2.6E-07	-4.7E-07	-3.7E-07	-3.9E-07	8.2E-06	-2.8E-07	-4.5E-07	-3.4E-07	-4.2E-07	-7.9E-07	-2.6E-07	
-1.5E-07	-1.1E-07	-1.7E-07	-2.6E-07	-3.8E-08	-1.5E-07	-1.4E-07	-1.4E-07	-2.6E-07	-2.3E-08	-1.8E-07	-1.2E-07	-1.3E-07	-2.8E-07	2.9E-06	-1.5E-07	-1.0E-07	-1.4E-07	-3.1E-07	-2.9E-08	
-2.7E-07	-2.1E-07	-2.7E-07	-4.2E-07	-1.3E-07	-2.7E-07	-2.4E-07	-2.5E-07	-4.1E-07	-1.3E-07	-2.9E-07	-2.2E-07	-2.3E-07	-4.5E-07	-1.5E-07	5.0E-06	-2.0E-07	-2.5E-07	-4.7E-07	-1.4E-07	
-2.0E-07	-1.6E-07	-2.1E-07	-3.2E-07	-8.4E-08	-2.0E-07	-1.8E-07	-1.9E-07	-3.2E-07	-8.4E-08	-2.2E-07	-1.6E-07	-1.8E-07	-3.4E-07	-1.0E-07	-2.0E-07	3.8E-06	-1.9E-07	-3.6E-07	-8.9E-08	
-2.4E-07	-2.0E-07	-2.5E-07	-3.9E-07	-1.1E-07	-2.4E-07	-2.2E-07	-2.3E-07	-3.9E-07	-1.1E-07	-2.7E-07	-2.0E-07	-2.2E-07	-4.2E-07	-1.4E-07	-2.5E-07	-1.9E-07	4.6E-06	-4.4E-07	-1.2E-07	
-4.6E-07	-3.9E-07	-4.7E-07	-7.4E-07	-2.6E-07	-4.7E-07	-4.2E-07	-4.4E-07	-7.2E-07	-2.8E-07	-5.0E-07	-3.9E-07	-4.0E-07	-7.9E-07	-3.1E-07	-4.7E-07	-3.6E-07	-4.4E-07	8.6E-06	-2.8E-07	
-1.3E-07	-9.1E-08	-1.4E-07	-2.4E-07	-2.5E-08	-1.3E-07	-1.2E-07	-1.2E-07	-2.4E-07	-9.6E-09	-1.5E-07	-9.7E-08	-1.1E-07	-2.6E-07	-2.9E-08	-1.4E-07	-8.9E-08	-1.2E-07	-2.8E-07	2.5E-06	

Table E7 Marginal Effect of Congestion for People younger than 35 yrs old, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal (rows)

-1.6E-06	1.1E-07	7.1E-08	1.8E-08	1.5E-07	7.8E-08	8.6E-08	9.1E-08	5.3E-09	1.7E-07	6.0E-08	1.1E-07	7.2E-08	2.1E-08	1.4E-07	7.8E-08	8.7E-08	9.0E-08	5.9E-09	1.7E-07
1.1E-07	-2.5E-06	1.3E-07	4.5E-08	2.2E-07	1.1E-07	1.4E-07	1.3E-07	4.1E-08	2.2E-07	1.1E-07	1.5E-07	1.3E-07	4.9E-08	2.2E-07	1.1E-07	1.5E-07	1.3E-07	4.1E-08	2.2E-07
7.1E-08	1.3E-07	-1.9E-06	2.9E-08	1.7E-07	9.0E-08	1.0E-07	1.1E-07	1.5E-08	1.9E-07	7.1E-08	1.3E-07	9.0E-08	3.2E-08	1.6E-07	9.0E-08	1.0E-07	1.1E-07	1.5E-08	1.9E-07
1.8E-08	4.5E-08	2.9E-08	-6.4E-07	7.4E-08	2.5E-08	3.8E-08	3.5E-08	-1.4E-08	7.4E-08	1.9E-08	4.5E-08	2.9E-08	-6.3E-09	6.8E-08	2.5E-08	3.8E-08	3.5E-08	-1.3E-08	7.5E-08
1.5E-07	2.2E-07	1.7E-07	7.4E-08	-3.5E-06	1.7E-07	2.0E-07	2.0E-07	5.3E-08	3.6E-07	1.5E-07	2.3E-07	1.7E-07	7.6E-08	3.5E-07	1.7E-07	2.0E-07	1.9E-07	5.3E-08	3.6E-07
7.8E-08	1.1E-07	9.0E-08	2.5E-08	1.7E-07	-1.9E-06	1.1E-07	9.8E-08	2.2E-08	1.8E-07	7.8E-08	1.1E-07	9.2E-08	2.9E-08	1.7E-07	8.5E-08	1.1E-07	9.8E-08	2.2E-08	1.8E-07
8.6E-08	1.4E-07	1.0E-07	3.8E-08	2.0E-07	1.1E-07	-2.2E-06	1.3E-07	2.2E-08	2.2E-07	8.5E-08	1.4E-07	1.1E-07	4.1E-08	1.9E-07	1.1E-07	1.2E-07	1.3E-07	2.2E-08	2.2E-07
9.1E-08	1.3E-07	1.1E-07	3.5E-08	2.0E-07	9.8E-08	1.3E-07	-2.2E-06	3.2E-08	1.9E-07	9.1E-08	1.3E-07	1.1E-07	3.9E-08	1.9E-07	9.8E-08	1.3E-07	1.2E-07	3.2E-08	1.9E-07
5.3E-09	4.1E-08	1.5E-08	-1.4E-08	5.3E-08	2.2E-08	2.2E-08	3.2E-08	-4.7E-07	7.3E-08	5.3E-09	4.1E-08	1.4E-08	-1.1E-08	5.1E-08	2.1E-08	2.2E-08	3.2E-08	-2.5E-08	7.4E-08
1.7E-07	2.2E-07	1.9E-07	7.4E-08	3.6E-07	1.8E-07	2.2E-07	1.9E-07	7.3E-08	-3.7E-06	1.7E-07	2.2E-07	1.9E-07	8.1E-08	3.4E-07	1.8E-07	2.2E-07	1.9E-07	7.2E-08	3.4E-07
6.0E-08	1.1E-07	7.1E-08	1.9E-08	1.5E-07	7.8E-08	8.5E-08	9.1E-08	5.3E-09	1.7E-07	-1.6E-06	1.1E-07	7.2E-08	2.2E-08	1.4E-07	7.8E-08	8.6E-08	9.0E-08	6.1E-09	1.7E-07
1.1E-07	1.5E-07	1.3E-07	4.5E-08	2.3E-07	1.1E-07	1.4E-07	1.3E-07	4.1E-08	2.2E-07	1.1E-07	-2.5E-06	1.3E-07	4.9E-08	2.2E-07	1.2E-07	1.5E-07	1.3E-07	4.0E-08	2.2E-07
7.2E-08	1.3E-07	9.0E-08	2.9E-08	1.7E-07	9.2E-08	1.1E-07	1.1E-07	1.4E-08	1.9E-07	7.2E-08	1.3E-07	-1.9E-06	3.2E-08	1.7E-07	9.2E-08	1.1E-07	1.1E-07	1.5E-08	1.9E-07
2.1E-08	4.9E-08	3.2E-08	-6.3E-09	7.6E-08	2.9E-08	4.1E-08	3.9E-08	-1.1E-08	8.1E-08	2.2E-08	4.9E-08	3.2E-08	-7.1E-07	7.2E-08	2.9E-08	4.1E-08	4.0E-08	-1.0E-08	8.1E-08
1.4E-07	2.2E-07	1.6E-07	6.8E-08	3.5E-07	1.7E-07	1.9E-07	1.9E-07	5.1E-08	3.4E-07	1.4E-07	2.2E-07	1.7E-07	7.2E-08	-3.4E-06	1.7E-07	2.0E-07	1.9E-07	5.1E-08	3.5E-07
7.8E-08	1.1E-07	9.0E-08	2.5E-08	1.7E-07	8.5E-08	1.1E-07	9.8E-08	2.1E-08	1.8E-07	7.8E-08	1.2E-07	9.2E-08	2.9E-08	1.7E-07	-1.9E-06	1.1E-07	9.8E-08	2.1E-08	1.8E-07
8.7E-08	1.5E-07	1.0E-07	3.8E-08	2.0E-07	1.1E-07	1.2E-07	1.3E-07	2.2E-08	2.2E-07	8.6E-08	1.5E-07	1.1E-07	4.1E-08	2.0E-07	1.1E-07	-2.2E-06	1.3E-07	2.2E-08	2.2E-07
9.0E-08	1.3E-07	1.1E-07	3.5E-08	1.9E-07	9.8E-08	1.3E-07	1.2E-07	3.2E-08	1.9E-07	9.0E-08	1.3E-07	1.1E-07	4.0E-08	1.9E-07	9.8E-08	1.3E-07	-2.1E-06	3.2E-08	1.9E-07
5.9E-09	4.1E-08	1.5E-08	-1.3E-08	5.3E-08	2.2E-08	2.2E-08	3.2E-08	-2.5E-08	7.2E-08	6.1E-09	4.0E-08	1.5E-08	-1.0E-08	5.1E-08	2.1E-08	2.2E-08	3.2E-08	-4.8E-07	7.3E-08
1.7E-07	2.2E-07	1.9E-07	7.5E-08	3.6E-07	1.8E-07	2.2E-07	1.9E-07	7.4E-08	3.4E-07	1.7E-07	2.2E-07	1.9E-07	8.1E-08	3.5E-07	1.8E-07	2.2E-07	1.9E-07	7.3E-08	-3.7E-06

Table E8 Marginal Effect of Congestion for People between 35 and 60 yrs old, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal (rows)

-1.9E-06	1.6E-07	9.7E-08	-5.4E-08	1.8E-07	1.2E-07	1.3E-07	1.0E-07	-6.2E-08	2.4E-07	9.0E-08	1.4E-07	8.6E-08	-3.8E-08	2.1E-07	9.5E-08	1.2E-07	1.3E-07	-6.8E-08	2.1E-07
1.6E-07	-3.5E-06	1.8E-07	4.6E-08	2.5E-07	2.2E-07	2.1E-07	2.0E-07	2.4E-08	3.3E-07	1.8E-07	2.3E-07	1.6E-07	7.3E-08	2.9E-07	1.9E-07	1.9E-07	2.2E-07	3.2E-08	3.0E-07
9.7E-08	1.8E-07	-2.2E-06	-4.5E-08	2.0E-07	1.4E-07	1.4E-07	1.2E-07	-5.6E-08	2.6E-07	1.0E-07	1.5E-07	9.7E-08	-2.5E-08	2.2E-07	1.1E-07	1.3E-07	1.5E-07	-6.6E-08	2.3E-07
-5.4E-08	4.6E-08	-4.5E-08	8.0E-07	1.0E-07	-1.7E-08	7.2E-09	-2.6E-08	-3.6E-07	1.5E-07	-5.3E-08	2.5E-08	-4.3E-08	-3.6E-07	1.1E-07	-3.6E-08	4.3E-09	-5.7E-09	-3.9E-07	1.3E-07
1.8E-07	2.5E-07	2.0E-07	1.0E-07	-3.8E-06	2.3E-07	2.2E-07	2.0E-07	8.5E-08	3.1E-07	2.0E-07	2.3E-07	1.8E-07	1.3E-07	2.8E-07	2.0E-07	2.0E-07	2.3E-07	9.7E-08	2.9E-07
1.2E-07	2.2E-07	1.4E-07	-1.7E-08	2.3E-07	-2.7E-06	1.8E-07	1.6E-07	-3.6E-08	3.0E-07	1.3E-07	1.9E-07	1.2E-07	4.0E-09	2.6E-07	1.5E-07	1.6E-07	1.8E-07	-3.4E-08	2.7E-07
1.3E-07	2.1E-07	1.4E-07	7.2E-09	2.2E-07	1.8E-07	-2.8E-06	1.5E-07	-6.2E-09	2.9E-07	1.4E-07	1.8E-07	1.3E-07	3.2E-08	2.5E-07	1.5E-07	1.6E-07	1.8E-07	-9.7E-09	2.6E-07
1.0E-07	2.0E-07	1.2E-07	-2.6E-08	2.0E-07	1.6E-07	1.5E-07	-2.4E-06	-4.7E-08	2.7E-07	1.1E-07	1.7E-07	1.0E-07	-4.6E-09	2.3E-07	1.3E-07	1.4E-07	1.6E-07	-4.9E-08	2.4E-07
-6.2E-08	2.4E-08	-5.6E-08	-3.6E-07	8.5E-08	-3.6E-08	-6.2E-09	-4.7E-08	1.1E-06	1.3E-07	-6.2E-08	3.3E-09	-5.2E-08	-3.7E-07	9.7E-08	-5.4E-08	-7.0E-09	-2.7E-08	-3.8E-07	1.1E-07
2.4E-07	3.3E-07	2.6E-07	1.5E-07	3.1E-07	3.0E-07	2.9E-07	2.7E-07	1.3E-07	-4.9E-06	2.6E-07	3.0E-07	2.3E-07	1.9E-07	3.6E-07	2.7E-07	2.5E-07	3.0E-07	1.5E-07	3.6E-07
9.0E-08	1.8E-07	1.0E-07	-5.3E-08	2.0E-07	1.3E-07	1.4E-07	1.1E-07	-6.2E-08	2.6E-07	-2.1E-06	1.5E-07	9.4E-08	-3.4E-08	2.2E-07	1.1E-07	1.3E-07	1.4E-07	-7.2E-08	2.3E-07
1.4E-07	2.3E-07	1.5E-07	2.5E-08	2.3E-07	1.9E-07	1.8E-07	1.7E-07	3.3E-09	3.0E-07	1.5E-07	-3.0E-06	1.4E-07	5.0E-08	2.6E-07	1.6E-07	1.6E-07	2.0E-07	5.9E-09	2.7E-07
8.6E-08	1.6E-07	9.7E-08	-4.3E-08	1.8E-07	1.2E-07	1.3E-07	1.0E-07	-5.2E-08	2.3E-07	9.4E-08	1.4E-07	-1.9E-06	-2.7E-08	2.0E-07	1.0E-07	1.1E-07	1.3E-07	-5.6E-08	2.0E-07
-3.8E-08	7.3E-08	-2.5E-08	-3.6E-07	1.3E-07	4.0E-09	3.2E-08	-4.6E-09	-3.7E-07	1.9E-07	-3.4E-08	5.0E-08	-2.7E-08	4.4E-07	1.5E-07	-1.6E-08	2.4E-08	1.7E-08	-4.0E-07	1.6E-07
2.1E-07	2.9E-07	2.2E-07	1.1E-07	2.8E-07	2.6E-07	2.5E-07	2.3E-07	9.7E-08	3.6E-07	2.2E-07	2.6E-07	2.0E-07	1.5E-07	-4.3E-06	2.3E-07	2.2E-07	2.6E-07	1.1E-07	3.2E-07
9.5E-08	1.9E-07	1.1E-07	-3.6E-08	2.0E-07	1.5E-07	1.5E-07	1.3E-07	-5.4E-08	2.7E-07	1.1E-07	1.6E-07	1.0E-07	-1.6E-08	2.3E-07	-2.3E-06	1.3E-07	1.6E-07	-5.8E-08	2.4E-07
1.2E-07	1.9E-07	1.3E-07	4.3E-09	2.0E-07	1.6E-07	1.6E-07	1.4E-07	-7.0E-09	2.5E-07	1.3E-07	1.6E-07	1.1E-07	2.4E-08	2.2E-07	1.3E-07	-2.5E-06	1.6E-07	-6.2E-09	2.3E-07
1.3E-07	2.2E-07	1.5E-07	-5.7E-09	2.3E-07	1.8E-07	1.8E-07	1.6E-07	-2.7E-08	3.0E-07	1.4E-07	2.0E-07	1.3E-07	1.7E-08	2.6E-07	1.6E-07	1.6E-07	-2.8E-06	-2.5E-08	2.7E-07
-6.8E-08	3.2E-08	-6.6E-08	-3.9E-07	9.7E-08	-3.4E-08	-9.7E-09	-4.9E-08	-3.8E-07	1.5E-07	-7.2E-08	5.9E-09	-5.6E-08	-4.0E-07	1.1E-07	-5.8E-08	-6.2E-09	-2.5E-08	1.1E-06	1.2E-07
2.1E-07	3.0E-07	2.3E-07	1.3E-07	2.9E-07	2.7E-07	2.6E-07	2.4E-07	1.1E-07	3.6E-07	2.3E-07	2.7E-07	2.0E-07	1.6E-07	3.2E-07	2.4E-07	2.3E-07	2.7E-07	1.2E-07	-4.4E-06

Table E9 Marginal Effect of Congestion for People > than 60 yrs old, $\frac{\partial P_i}{\partial c_i}$, diagonal (in bold), $\frac{\partial P_i}{\partial c_j}$, off diagonal (columns), $\frac{\partial P_j}{\partial c_i}$, off diagonal

rows)

2.3E-05	-8.9E-07	-9.5E-07	-2.3E-06	-7.6E-07	-1.2E-06	-8.2E-07	-1.1E-06	-2.3E-06	-6.6E-07	-1.1E-06	-9.2E-07	-1.1E-06	-2.1E-06	-6.1E-07	-1.3E-06	-9.9E-07	-1.0E-06	-2.0E-06	-6.9E-07
-8.9E-07	1.6E-05	-7.1E-07	-1.5E-06	-6.1E-07	-8.5E-07	-6.3E-07	-7.9E-07	-1.5E-06	-5.1E-07	-7.9E-07	-7.0E-07	-8.6E-07	-1.4E-06	-4.8E-07	-8.8E-07	-7.8E-07	-7.6E-07	-1.3E-06	-5.3E-07
-9.5E-07	-7.1E-07	1.8E-05	-1.7E-06	-5.9E-07	-9.2E-07	-6.7E-07	-8.5E-07	-1.6E-06	-5.2E-07	-8.6E-07	-7.4E-07	-8.9E-07	-1.6E-06	-5.0E-07	-9.5E-07	-7.8E-07	-8.2E-07	-1.5E-06	-5.4E-07
-2.3E-06	-1.5E-06	-1.7E-06	4.4E-05	-1.2E-06	-2.3E-06	-1.4E-06	-1.9E-06	-6.1E-06	-1.1E-06	-2.1E-06	-1.6E-06	-2.0E-06	-5.8E-06	-9.8E-07	-2.4E-06	-1.7E-06	-1.8E-06	-5.3E-06	-1.1E-06
-7.6E-07	-6.1E-07	-5.9E-07	-1.2E-06	1.4E-05	-7.2E-07	-5.4E-07	-6.9E-07	-1.2E-06	-4.8E-07	-6.5E-07	-6.3E-07	-7.9E-07	-1.1E-06	-4.2E-07	-7.5E-07	-7.3E-07	-6.6E-07	-9.7E-07	-5.1E-07
-1.2E-06	-8.5E-07	-9.2E-07	-2.3E-06	-7.2E-07	2.2E-05	-7.9E-07	-1.0E-06	-2.2E-06	-6.2E-07	-1.1E-06	-8.8E-07	-1.1E-06	-2.1E-06	-5.8E-07	-1.2E-06	-9.5E-07	-9.9E-07	-2.0E-06	-6.4E-07
-8.2E-07	-6.3E-07	-6.7E-07	-1.4E-06	-5.4E-07	-7.9E-07	1.5E-05	-7.4E-07	-1.4E-06	-4.8E-07	-7.5E-07	-6.5E-07	-7.8E-07	-1.3E-06	-4.5E-07	-8.2E-07	-7.0E-07	-7.1E-07	-1.2E-06	-5.0E-07
-1.1E-06	-7.9E-07	-8.5E-07	-1.9E-06	-6.9E-07	-1.0E-06	-7.4E-07	2.0E-05	-1.9E-06	-5.8E-07	-9.5E-07	-8.2E-07	-1.0E-06	-1.7E-06	-5.4E-07	-1.1E-06	-9.0E-07	-9.1E-07	-1.6E-06	-6.1E-07
-2.3E-06	-1.5E-06	-1.6E-06	-6.1E-06	-1.2E-06	-2.2E-06	-1.4E-06	-1.9E-06	4.3E-05	-1.1E-06	-2.1E-06	-1.6E-06	-2.0E-06	-5.6E-06	-9.7E-07	-2.3E-06	-1.7E-06	-1.8E-06	-5.1E-06	-1.1E-06
-6.6E-07	-5.1E-07	-5.2E-07	-1.1E-06	-4.8E-07	-6.2E-07	-4.8E-07	-5.8E-07	-1.1E-06	1.2E-05	-5.8E-07	-5.3E-07	-6.6E-07	-9.5E-07	-3.6E-07	-6.4E-07	-6.1E-07	-5.6E-07	-8.9E-07	-4.1E-07
-1.1E-06	-7.9E-07	-8.6E-07	-2.1E-06	-6.5E-07	-1.1E-06	-7.5E-07	-9.5E-07	-2.1E-06	-5.8E-07	2.1E-05	-8.2E-07	-9.9E-07	-2.0E-06	-5.5E-07	-1.1E-06	-8.6E-07	-9.2E-07	-1.8E-06	-6.0E-07
-9.2E-07	-7.0E-07	-7.4E-07	-1.6E-06	-6.3E-07	-8.8E-07	-6.5E-07	-8.2E-07	-1.6E-06	-5.3E-07	-8.2E-07	1.7E-05	-9.0E-07	-1.4E-06	-5.0E-07	-9.1E-07	-8.1E-07	-7.9E-07	-1.3E-06	-5.6E-07
-1.1E-06	-8.6E-07	-8.9E-07	-2.0E-06	-7.9E-07	-1.1E-06	-7.8E-07	-1.0E-06	-2.0E-06	-6.6E-07	-9.9E-07	-9.0E-07	2.1E-05	-1.8E-06	-5.9E-07	-1.1E-06	-1.0E-06	-9.8E-07	-1.6E-06	-6.9E-07
-2.1E-06	-1.4E-06	-1.6E-06	-5.8E-06	-1.1E-06	-2.1E-06	-1.3E-06	-1.7E-06	-5.6E-06	-9.5E-07	-2.0E-06	-1.4E-06	-1.8E-06	4.1E-05	-8.9E-07	-2.2E-06	-1.5E-06	-1.7E-06	-4.9E-06	-9.9E-07
-6.1E-07	-4.8E-07	-5.0E-07	-9.8E-07	-4.2E-07	-5.8E-07	-4.5E-07	-5.4E-07	-9.7E-07	-3.6E-07	-5.5E-07	-5.0E-07	-5.9E-07	-8.9E-07	1.1E-05	-6.0E-07	-5.4E-07	-5.2E-07	-8.5E-07	-3.8E-07
-1.3E-06	-8.8E-07	-9.5E-07	-2.4E-06	-7.5E-07	-1.2E-06	-8.2E-07	-1.1E-06	-2.3E-06	-6.4E-07	-1.1E-06	-9.1E-07	-1.1E-06	-2.2E-06	-6.0E-07	2.3E-05	-9.9E-07	-1.0E-06	-2.0E-06	-6.7E-07
-9.9E-07	-7.8E-07	-7.8E-07	-1.7E-06	-7.3E-07	-9.5E-07	-7.0E-07	-9.0E-07	-1.7E-06	-6.1E-07	-8.6E-07	-8.1E-07	-1.0E-06	-1.5E-06	-5.4E-07	-9.9E-07	1.8E-05	-8.6E-07	-1.4E-06	-6.3E-07
-1.0E-06	-7.6E-07	-8.2E-07	-1.8E-06	-6.6E-07	-9.9E-07	-7.1E-07	-9.1E-07	-1.8E-06	-5.6E-07	-9.2E-07	-7.9E-07	-9.8E-07	-1.7E-06	-5.2E-07	-1.0E-06	-8.6E-07	1.9E-05	-1.6E-06	-5.8E-07
-2.0E-06	-1.3E-06	-1.5E-06	-5.3E-06	-9.7E-07	-2.0E-06	-1.2E-06	-1.6E-06	-5.1E-06	-8.9E-07	-1.8E-06	-1.3E-06	-1.6E-06	-4.9E-06	-8.5E-07	-2.0E-06	-1.4E-06	-1.6E-06	3.8E-05	-9.3E-07
-6.9E-07	-5.3E-07	-5.4E-07	-1.1E-06	-5.1E-07	-6.4E-07	-5.0E-07	-6.1E-07	-1.1E-06	-4.1E-07	-6.0E-07	-5.6E-07	-6.9E-07	-9.9E-07	-3.8E-07	-6.7E-07	-6.3E-07	-5.8E-07	-9.3E-07	1.3E-05

Table E10 Reported Z-scores from Difference in Means Tests of Marginal Effects Between Groups¹¹³

	Group	Opportunity Costs	Children	Age	Age	Age
Choice	Marginal Effect	High – Low	No kids - kids	Midlife – old	Midlife – young	Young – old
Private AM	$\partial P_1 / \partial c_1$	-1.13	-6.74 *	-4.39 *	-0.10	-4.38 *
Private Offpeak	$\partial P_2 / \partial c_2$	-1.16	-6.66 *	-4.80 *	-0.35	-4.69 *
Private Lunch	$\partial P_3 / \partial c_3$	-1.11	-6.76 *	-4.54 *	-0.09	-4.64 *
Private PM	$\partial P_4 / \partial c_4$	-1.36*	-6.38 *	-3.92 *	0.47	-4.13 *
Private Evening	$\partial P_5 / \partial c_5$	-0.62	-6.20 *	-4.27 *	-0.08	-3.90 *
Amuse AM	$\partial P_6 / \partial c_6$	-1.29*	-6.63 *	-4.35 *	-0.29	-4.32 *
Amuse Offpeak	$\partial P_7 / \partial c_7$	-1.07	-6.66 *	-4.78 *	-0.20	-4.72 *
Amuse Lunch	$\partial P_8 / \partial c_8$	-1.13	-6.77 *	-4.56 *	-0.07	-4.65 *
Amuse PM	$\partial P_9 / \partial c_9$	-1.29 *	-6.46 *	-3.92 *	0.52	-4.13 *
Amuse Evening	$\partial P_{10} / \partial c_{10}$	-0.87	-6.06 *	-4.57 *	-0.41	-4.10 *
Shop AM	$\partial P_{11} / \partial c_{11}$	-1.21	-6.69 *	-4.34 *	-0.15	-4.37 *
Shop Offpeak	$\partial P_{12} / \partial c_{12}$	-1.10	-6.70 *	-4.79 *	-0.18	-4.77 *
Shop Lunch	$\partial P_{13} / \partial c_{13}$	-0.99	-6.86 *	-4.47 *	0.003	-4.46 *
Shop PM	$\partial P_{14} / \partial c_{14}$	-1.44 *	-6.27 *	-3.82 *	0.36	-4.03 *
Shop Evening	$\partial P_{15} / \partial c_{15}$	-0.78	-6.06 *	-4.55 *	-0.26	-4.03 *
Meals AM	$\partial P_{16} / \partial c_{16}$	-1.23	-6.74 *	-4.33 *	-0.14	-4.36 *
Meals Offpeak	$\partial P_{17} / \partial c_{17}$	-0.95	-6.75 *	-4.62 *	-0.09	-4.47 *
Meals Lunch	$\partial P_{18} / \partial c_{18}$	-1.2	-6.73 *	-4.57 *	-0.24	-4.59 *
Meals PM	$\partial P_{19} / \partial c_{19}$	-1.40 *	-6.41 *	-3.76 *	0.49	-4.06 *
Meals Evening	$\partial P_{20} / \partial c_{20}$	-0.81	-6.09 *	-4.54 *	-0.24	-4.17 *

¹¹³ Asterisks represent significance for alpha = .10 for a one-tailed test.

Table E11 The Conversion of the Effect of an Additional Car on Time

Demographic Groups	Time Periods	Effect of Additional Cars on Speed(MPH)	Effect of Additional Cars on Time(minutes)	MC of Additional Car (\$/car)	\$/Hour
High Opportunity Cost	AM	-3.6 mph	1.21 minutes	\$0.01247	\$0.90
	Off	-3.029 mph	1.06		\$0.79
	Lunch	-3.372 mph	0.29		\$0.22
	PM	-4.515 mph	2.29		\$1.71
	Evening	-2.05 mph	0.97		\$0.73
Low Opportunity Cost	AM	-3.6 mph	1.21 minutes	\$0.009	\$0.65
	Off	-3.029 mph	1.06		\$0.57
	Lunch	-3.372 mph	0.29		\$0.16
	PM	-4.515 mph	2.29		\$1.24
	Evening	-2.05 mph	0.97		\$0.52
No Children	AM	-3.6 mph	1.21 minutes	\$0.051	\$3.70
	Off	-3.029 mph	1.06		\$3.24
	Lunch	-3.372 mph	0.29		\$0.89
	PM	-4.515 mph	2.29		\$7.01
	Evening	-2.05 mph	0.97		\$2.97
At Least One Child	AM	-3.6 mph	1.21 minutes	\$-0.013	\$-0.94
	Off	-3.029 mph	1.06		\$-0.83
	Lunch	-3.372 mph	0.29		\$-0.23
	PM	-4.515 mph	2.29		\$-1.79
	Evening	-2.05 mph	0.97		\$-0.76
Young Age < 35 yrs old	AM	-3.6 mph	1.21 minutes	\$0.0413	\$2.99
	Off	-3.029 mph	1.06		\$2.63
	Lunch	-3.372 mph	0.29		\$0.72
	PM	-4.515 mph	2.29		\$5.67
	Evening	-2.05 mph	0.97		\$2.40
Medium Age B/W 35 & 60	AM	-3.6 mph	1.21 minutes	\$0.005	\$0.36
	Off	-3.029 mph	1.06		\$0.32
	Lunch	-3.372 mph	0.29		<\$0.01
	PM	-4.515 mph	2.29		\$0.69
	Evening	-2.05 mph	0.97		\$0.29
Old Age >60 yrs old	AM	-3.6 mph	1.21 minutes	\$0.0226	\$1.64
	Off	-3.029 mph	1.06		\$1.44
	Lunch	-3.372 mph	0.29		\$0.39
	PM	-4.515 mph	2.29		\$3.11
	Evening	-2.05 mph	0.97		\$1.31